SSM - Population Health 25 (2024) 101624

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: www.elsevier.com/locate/ssmph

When money and mental health problems pile up: The reciprocal relationship between income and psychological distress

Oscar Jiménez-Solomon [a,b,*], Garfinkel Irwin [a], Wall Melanie [c,d], Wimer Christopher [a]

[a] Center on Poverty and Social Policy, School of Social Work, Columbia University, 1255 Amsterdam Avenue, New York, NY, 10027, USA
[b] New York State Center of Excellence for Cultural Competence, New York State Psychiatric Institute, Columbia University Irving Medical Center, 1051 Riverside Drive, Unit 69, New York, NY, 10032, USA
[c] Department of Psychiatry, Columbia University, 1051 Riverside Drive, Unit 48, New York, NY, 10032, USA
[d] Department of Biostatistics, Mailman School of Public Health, Columbia University, 722 West 168th Street, R207, New York, NY, 10032, USA

A B S T R A C T

Background: Longitudinal studies suggest that socioeconomic status (SES) and mental health have a bidirectional relationship such that SES declines lead to a deterioration of mental health (*social causation*), while worsening mental health leads to SES declines (*social drift*). However, the dynamic relationship between income and psychological distress has not been sufficiently studied.

Methods: We use cross-lagged panel models with unit fixed effects (FE-CLPM) and data from a five-wave representative panel (n = 3103) of working-age (18–64) New York City adults. Yearly measures include individual earnings, family income (income-to-needs), and psychological distress. We also examine effects by age, gender, education, and racial/ethnic identification.

Results: We find significant bidirectional effects between earnings and distress. Increases in past-year individual earnings decrease past-month psychological distress (*social causation effect [SCE]*, standardized β= −0.07) and increases in psychological distress reduce next-year individual earnings (*social drift effect [SDE]*, β= −0.03). Family income and distress only have a unidirectional relationship from past-year family income to distress (*SCE*, β= -.03). Strongest evidence of bidirectional effects between earnings and distress is for prime working-age individuals (*SCE*, β= −0.1; *SDE*, β= −0.03), those with less than bachelor's degrees (*SCE*, β= −0.08; *SDE*, β= −0.05), and Hispanics (*SCE*, β= −0.06; *SDE*, β= −0.08). We also find evidence of reciprocal effects between family income and distress for women (*SCE*, β= −0.03; *SDE*, β= −0.05), and Hispanics (*SDE*, β= −0.04; *SDE*, β= −0.08).

Conclusions: Individual earnings, which are labor market indicators, may be stronger social determinants of mental health than family income. However, important differences in social causation and social drift effects exist across groups by age, education, gender, and racial/ethnic identities. Future research should examine the types of policies that may buffer the mental health impact of negative income shocks and the declines in income associated with worsening mental health, especially among the most vulnerable.

1. Introduction

The association between socioeconomic status (SES) and mental health has been well-documented by decades of sociological and epidemiological research (Dohrenwend & Dohrenwend, 1969; Reiss, 2013). Individuals who are worse off in society are more likely to experience poor mental health than those who are better off. For example, those with lower income, less wealth, and living in material deprivation are at a higher risk of experiencing psychological distress, depression, anxiety, and other psychiatric conditions compared to those better off in society (Kiely, Leach, Olesen, & Butterworth, 2015; Spivak, Cullen, Eaton, Rodriguez, & Mojtabai, 2019).

Despite the overwhelming evidence linking SES to mental health, the direction of causality has been a long-standing debate in social sciences and psychiatric epidemiology (Mossakowski, 2014, pp. 2154–2160). Two theories have offered competing explanations for the association between SES and mental health.

The first theory is *social causation*, which posits that low SES causes mental health to deteriorate over time (Hudson, 2005). Low SES would worsen mental health by exposing individuals to low income, material hardship (Heflin & Iceland, 2009; Kiely et al., 2015), such as housing (Bentley, Baker, & Mason, 2012; Hudson, 2005) and food insecurity (Elgar et al., 2021), and over-indebtedness (Fitch, Hamilton, Bassett, & Davey, 2011), which in turn would trigger a stress process (Aneshensel, 2009) and an erosion of protective psychological factors (e.g., personal agency, self-esteem, hope) to cope with life stressors (Frankham, Richardson, & Maguire, 2020; Jiménez-Solomon et al., 2022).

The second theory is *social drift*, which proposes that an individual's

* Corresponding author. 1255 Amsterdam Avenue, New York, NY, 10027, USA.
E-mail address: ogj2102@columbia.edu (O. Jiménez-Solomon).

https://doi.org/10.1016/j.ssmph.2024.101624
Received 24 September 2023; Received in revised form 5 February 2024; Accepted 7 February 2024
Available online 8 February 2024

worsening mental health causes their SES to drift downward (Johnson, Cohen, Dohrenwend, Link, & Brook, 1999; Muntaner, Eaton, Miech, & O'Campo, 2004). This can occur due to loss of employment and income (Ridley, Rao, Schilbach, & Patel, 2020), loss of productivity (e.g., reduced number of days worked) (Mall et al., 2015), employment stigma and discrimination (Sharac, McCrone, Clement, & Thornicroft, 2010), and increased healthcare expenses (Jin, Zhu, & He, 2020). For children and adolescents, emotional and behavioral problems would predict lower educational attainment in young adulthood (Johnson et al., 1999).

Over the past decade, longitudinal studies have increasingly found evidence that the relationship between SES and mental health is bidirectional, suggesting that both *social causation* and *social drift* theories have merit (Mossakowski, 2014, pp. 2154–2160). For example, studies have identified bidirectional relationships between consumption poverty and depression (Jin et al., 2020), financial difficulties and psychological distress (Gorgievski, Bakker, Schaufeli, van der Veen, & Giesen, 2010), individual and household assets with depression (Lund & Cois, 2018), difficulty meeting unexpected expenses and psychological distress (Darin-Mattsson, Andel, Celeste, & Kåreholt, 2018), wealth and depression (Ahrenfeldt & Möller, 2021), food insecurity and psychological distress (Kim-Mozeleski, Poudel, & Tsoh, 2021), and financial hardship and psychological distress (O'Donnell, Stuart, & O'Donnell, 2020). Collectively, this empirical evidence supports an emerging theory postulating that the relationship between SES and mental health is intrinsically reciprocal. Low SES and ill mental health would create a cycle of cumulative disadvantage leading to increasing mental health deterioration and socioeconomic decline over time (Anakwenze & Zuberi, 2013; Mossakowski, 2014, pp. 2154–2160).

Despite the growing number of studies indicating that the relationship between SES and mental health is reciprocal, the existing literature has several substantive gaps and methodological limitations.

1.1. Substantive gaps in the literature

Studies examining the relationship between SES and health have employed a diverse range of SES indicators, often leading to different conclusions. Most notably, studies using labor market indicators (e.g., wages, employment) provide support for both social causation and social drift dynamics, while those using non-labor indicators (e.g., household income, education) provide evidence in support of social causation effects only (Kröger, Pakpahan, & Hoffmann, 2015). Illness is likely to affect labor productivity, employability, and career advancement, (Mall et al., 2015), but its effect on non-labor market outcomes is less pronounced. Earnings from other family members, other sources of income, and cash transfers in response to decreases in earnings may serve as buffers to individual earnings losses (Ng & Tan, 2021). Adult educational outcomes may not be as affected by health changes since for most people education is completed by early adulthood (Kröger et al., 2015).

Nevertheless, the dynamic relationships between labor and non-labor market indicators, respectively, *and* mental health have not been sufficiently studied, leaving a significant substantive gap in the research about the social determinants of mental health.

Another limitation in the research about SES and mental health is its insufficient attention to potential inequities. Previous studies in this area have not sufficiently examined differences in the magnitude and direction of social causation and social drift effects across subpopulation. Studies often estimate "average effects," failing to investigate how effects vary across subgroups defined by age, gender, racial/ethnic identification, and other important sources of stratification (Kim-Mozeleski et al., 2021; O'Donnell et al., 2020). This is an important gap in the research because the relationship between SES and mental health is likely to differ among these subgroups, as discussed below.

Age. Research suggests that the relationship between SES and mental health changes over the life course. Different dimensions of SES and mental health seem to interact over the life course creating reciprocal dynamics and cumulative disadvantage. Low SES in early life heightens exposure to stress with the potential of causing epigenetic changes that increase the vulnerability to experiencing extreme psychological pain, depression, and other forms of psychological distress (Mann & Rizk, 2020). Emotional disturbances and disruptive behaviors in childhood and depression in adolescence lead to lower educational attainment in young adulthood (Clayborne, Varin, & Colman, 2019), while lower education and material hardship in the household in young adulthood increase the risk for depression, anxiety, and other forms of psychological distress in middle-age (McKee-Ryan, Song, Wanberg, & Kinicki, 2005). Mental health deterioration in early middle-age seems to cause further SES declines through unemployment, loss of productivity, and increased expenditures (Jin et al., 2020), and a cascade of mental health, physical health and economic decline later in life (Kivimäki et al., 2020). Hence, different social causation and social drift mechanisms are likely to play varying roles over the life course.

Gender. Compared to men, women report significantly higher levels of psychological distress, depression, and anxiety (Viertiö et al., 2021). Moreover, the interaction between SES and gender increase risk of depression (Muntaner et al., 2004), such that women have higher prevalence of depression given the same level of household income (Assari, 2017). However, the relationship between gender, SES, and mental health is complex. Although low SES women may face more stressors than men, the mechanisms affecting women and men are likely to differ (Viertiö et al., 2021). For instance, social relationships may have a stronger protective effect for women (Elliott, 2001). Also, men continue to face strong gender expectations to be the family breadwinners during their working years (Townsend, 2002), which may explain the strong effect of income trajectories on the mental health of middle-age men (Frech & Damaske, 2019).

Education. Research has consistently shown that higher levels of education are associated with higher income and better mental health. The causal effect of education on earnings has been long understood (Card, 1999). For instance, higher education has been found to have persistent positive effects on earnings over the life course (Tamborini, Kim, Sakamoto, & Sakamoto, 2015). Conversely, research has also found a causal effect of family income on educational attainment (Blanden & Gregg, 2004). Research has also long documented the relationship between education and mental health. For instance, recent research finds that each additional year of education significantly decreases the likelihood of depression and anxiety over two decades (Kondirolli & Sunder, 2022). Similarly, a recent large-scale study finds that lower educational attainment causally increases the risk for major depression, generalized anxiety disorders, ADHD and PTSD, and a reverse causal effect for ADHD, suggesting that mental health problems in childhood and young adulthood can also impact educational attainment (Demange, Boomsma, van Bergen, & Nivard, 2023).

Race/ethnicity. The relationship between race/ethnicity, SES, and mental health is complex and multifaceted. Despite being between two and three times more likely to live in poverty and less likely to have a bachelor's degree or higher education than non-Hispanic Whites, some studies find that Blacks and Hispanics have a lower prevalence of depression than non-Hispanic Whites, while others report higher (Williams, Mohammed, Leavell, & Collins, 2010). The difference seems to depend on whether studies adjust for SES indicators and other factors that may be in the causal pathway (Ettman, Cohen, Abdalla, & Galea, 2020). For example, after controlling for income, homeownership, and education, Blacks and Hispanics have significantly lower odds of depression than non-Hispanic Whites (Williams et al., 2010). These findings suggest that SES indicators are not confounders of the relationship between race/ethnicity and mental health but key mediators instead. Racism, discrimination, and other structural inequities affecting Blacks, Hispanics and other minoritized groups, are likely to affect mental health through inequities in income, employment, and educational opportunities.

Consequently, it is essential that research about the relationships between SES indicators and mental health examine potential differences in the magnitude and direction of effects among age, gender, education, and racial/ethnic groups.

1.2. Methodological limitations in the literature

Studies examining the relationship between SES and mental health often rely on research designs with limited ability to estimate causal effects. Some studies fail to examine simultaneously social causation and social drift effects. Other studies account for 'reverse causation' but do not control for unobserved differences between individuals. For example, some studies provide estimates of causal effects by controlling for unobserved differences though experimental or quasi-experimental designs, but do not simultaneously test both directions of causality (McGuire, Kaiser, & Bach-Mortensen, 2022; Ridley et al., 2020). Conventional cross-lagged panel models (CLPMs) estimate reciprocal effects between SES and mental health simultaneously (Gorgievski et al., 2010; Kim-Mozeleski et al., 2021), but they do not control for unobserved differences among individuals. This limitation is crucial since changes in SES and mental health may be driven by unobserved characteristics among individuals (e.g., genetics, psychological traits). To address this limitation in the research examining social causation and social drift hypotheses, Kröger and colleagues recommend that: (1) studies estimate both directions of causality in simultaneous equations; and (2) utilize statistical methods that control for unobserved differences between individuals that are stable over time (Kröger et al., 2015).

1.3. The present study

This study contributes to the literature on the dynamic relationships between SES and mental health by addressing substantive and methodological gaps in existent research. Substantively, this study examines the longitudinal relationship between income and mental health utilizing labor market and non-labor income measures likely to have different dynamic relationships with mental health outcomes: individual earnings and family income. To address another important substantive gap in the literature, this study examines differences in the effects between income and mental health across groups defined by age, gender, level of education, and racial/ethnic identity.

Methodologically, this study leverages novel structural equation modeling statistical techniques that integrate CLPMs with unit fixed effects and effectively address two important threats to casual inference by: (1) simultaneously estimating *social causation* and *social drift* effects, thus controlling for reverse causation; and (2) estimating effects based only on within-person changes, thereby controlling for stable differences among individuals (Allison, Williams, & Moral-Benito, 2017; Leszczensky & Wolbring, 2019).

To our knowledge, this is the first study to examine the longitudinal dynamics between individual-level measures of income and mental health using a CLPM with fixed effects. One recent study has examined effects between financial hardship and psychological distress using a CLPM with random intercepts (O'Donnell et al., 2020), which also estimates effects based on within-person changes, but it does not examine the role of income. Another study has investigated the reciprocal relationship between income and subjective wellbeing using a CLPM with fixed effects. However, it did not focus on a mental health measure per se and relied on national aggregate data and not individual measures (Zyphur et al., 2020).

2. Materials and methods

2.1. Data and analytic sample

We utilize panel data from the New York City Longitudinal Study of Wellbeing (also known as the "Poverty Tracker"). The data come from a representative sample of New York City adults surveyed at baseline and every twelve months about their economic and mental health wellbeing between 2015 and 2019. Details on the sampling and survey schedule have been described in detail elsewhere (Collyer et al., 2023). For this paper, our analytic sample includes working-age adults between 18 and 64 years of age (n = 3103). We utilize data from five waves: baseline (n = 3103) and follow-up surveys at 12-months (n = 2503), 24-months (n = 2332), 36-months (n = 2154), and 48-months (n = 2037). We utilize full information maximum likelihood estimation (FIML) to handle missing data in our cross-lagged panel models. Within a structural equation modeling (SEM) framework, FIML allows for the estimation of effects for cases with data on the dependent variable and at least some data on predictors. FIML is more efficient than listwise deletion, pairwise deletion, and similar response pattern imputation, producing less-biased estimates and more precise standard errors, yielding the lowest rates of convergence failures and near-optimal Type 1 error rates (Enders & Bandalos, 2001; Moral-Benito, 2013). Additionally, FIML performs well even in the presence of highly persistent processes (e.g., "unit roots" or "integrated" processes) (Allison et al., 2017; Moral-Benito, 2013).

2.2. Measures

Psychological distress. Our mental health measure is the Kessler-6 distress scale (K6), a six-item inventory used as a measure of global psychological distress based on self-reported symptoms of anxiety and depression over the prior 30 days (Kessler et al., 2010). With range values 0–24, higher scores indicate higher levels of distress. Following other studies, we analyze the K6 as a continuous variable by transforming it into its natural log to account for its skewed distribution (Tomitaka et al., 2017). We use a continuous, measure of global psychological distress, as opposed to disorder specific measures, to examine the dynamic relationship between changes in income and population mental health.

Individual earnings. Respondents who reported at least one month of work over the past 12 months at each wave were asked to report their total earnings over the same period. Responses were predominately given in continuous dollar amounts, however a minority of participants (e.g., 11% at baseline) preferred to give total earnings categorically (i.e., "less than $5,000," "$5000 to $9,999," "$10,000 to $14,999," … "or, over $150,000") or left earnings completely missing (e.g., 5% at baseline). To harmonize continuous and categorical responses for total earnings, categorical responses were converted to continuous responses using multiple imputation leveraging the distribution of the continuous values for respondents in the same earnings bracket. For respondents who did not enter a dollar amount or a bracket, we directly imputed a positive dollar amount for respondents who reported working in the past 12 months. Individuals who reported no paid work were assigned zero earnings (Collyer et al., 2023). Consistent with prior studies and recommendations for modeling earnings, we used the within sample percentile ranks from 1 to 100 based on the individual's reported or imputed earnings (Chetty et al., 2016). Hence, our estimates are not based changes in the dollar amount of earnings per se but changes in the ranking order of earnings, that is, the relative position of an individual's earnings with respect to the earnings of all others in the sample.

Family Income-to-Needs Ratio. We use the Supplemental Poverty Measure (SPM) Income-to-Needs ratio, as a measure of family income. This measure is estimated by dividing the family unit's income over the prior 12 months by their needs. SPM income is the sum of all sources of post-tax cash income (e.g., earnings, unemployment, cash government benefits) *plus* in-kind government benefits (e.g., food stamps, housing subsidies) *minus* nondiscretionary expenses (e.g., medical out-of-pocket expenses, work expenses). SPM needs refer to the estimated amount a family of a given household size and location (New York City) needs to meet their basic needs (e.g., food, clothing, shelter, and utilities), based on the most recent five years of expenditure data (Fox, 2017). The SPM income-to-needs ratio is regarded as a superior measure of poverty, relative to the Official Poverty Measure, which is based on a set amount (three times the cost of a basic food diet in 1963) (Congressional Research Service, 2022). For this analysis, we utilize the natural log of the income-to-needs ratio (hereafter family income) to reduce asymmetry in the income distribution.

2.3. Analytic strategy

All models were estimated using Mplus software version 8.7 Mplus. Mplus provides a powerful and flexible platform to conduct structural equation modeling with latent variables, and utilizing maximum likelihood estimation to handle missing data (Muthén and Muthén (1998-2017)). Mplus has also been used in testing the most recent innovations in cross-lagged panel models with unit effects (Zyphur et al., 2020).

We employ cross-lagged panel models with unit fixed effects (FE-CLPM) as our main analytic strategy (Allison et al., 2017; Zyphur et al., 2020). FE-CLPMs offer several advantages. In conventional CLPMs coefficients estimate how much individuals fluctuate with respect to the group mean for *X* and *Y* under the assumption that there are no stable between-person differences in these variables (Mund & Nestler, 2019). In FE-CLPMs, cross-lagged coefficients refer to the extent to which a deviation from a person-specific mean in *X* (e.g., earnings) is associated with subsequent deviations from a person-specific mean in *Y* (e.g., psychological distress). Thus, FE-CLPM controls for all time-invariant confounders observed and unobserved (Leszczensky & Wolbring, 2019). FE-CLPMs provide one additional advantage over other panel models. FE-CLPMs can help overcome the problem of mis-specified temporal lags. FE-CLPMs can correctly identify both the contemporaneous and the lagged effect of *X*, when both of them are included in the model (Leszczensky & Wolbring, 2019). This feature will be especially helpful in examining the effect on distress of past-year income assessed contemporaneously and a year prior.

Our basic FE-CLPM model (Fig. 1) is specified in a structural equation modeling framework by creating two latent variables $\eta^{(x)}$ and $\eta^{(y)}$. These latent variables capturing the commonality within each individual in their *X* (individual earnings or family income-to-needs) and *Y* (psychological distress) values across all timepoints. This commonality has been referred to as a “random intercept” (Hamaker, Kuiper, & Grasman, 2015). By including the covariance between these latent factors, the FE-CLPM controls for stable factors and holds them constant across observations, effectively operating as what the econometrics literature refers to as “fixed effects” (Zyphur et al., 2020). Conceptually, these stable factors refer to time-invariant individual-specific factors affecting their values of *X* and *Y*, such as psychological traits, genetic predispositions, and time-invariant family or neighborhood stressors (Mund & Nestler, 2019).

Model specification. Our basic model examines the cross-lagged effects between one of two income measures (individual earnings or family income) and psychological distress among working-age adults (See Table 2). Theory and prior empirical research provide some basis to hypothesize the temporal lagged effect of income changes on distress. In recent meta-analyses about the impact of cash transfers on mental health, most studies document a significant effect of income changes after 1 to 2 years (McGuire et al., 2022; Ridley et al., 2020). The stress-process theory and empirical research indicate that financial strain is a key mediator between income and psychological distress (Aneshensel, 2009). From this perspective, it would be expected that the effect of income changes on mental health would not be instantaneous, and instead develop as patterns of consumption change significantly to increase or decrease financial strain. Given these conceptual and empirical considerations, we simultaneously include measures of income at two timepoints as predictors of distress in the model: (a)

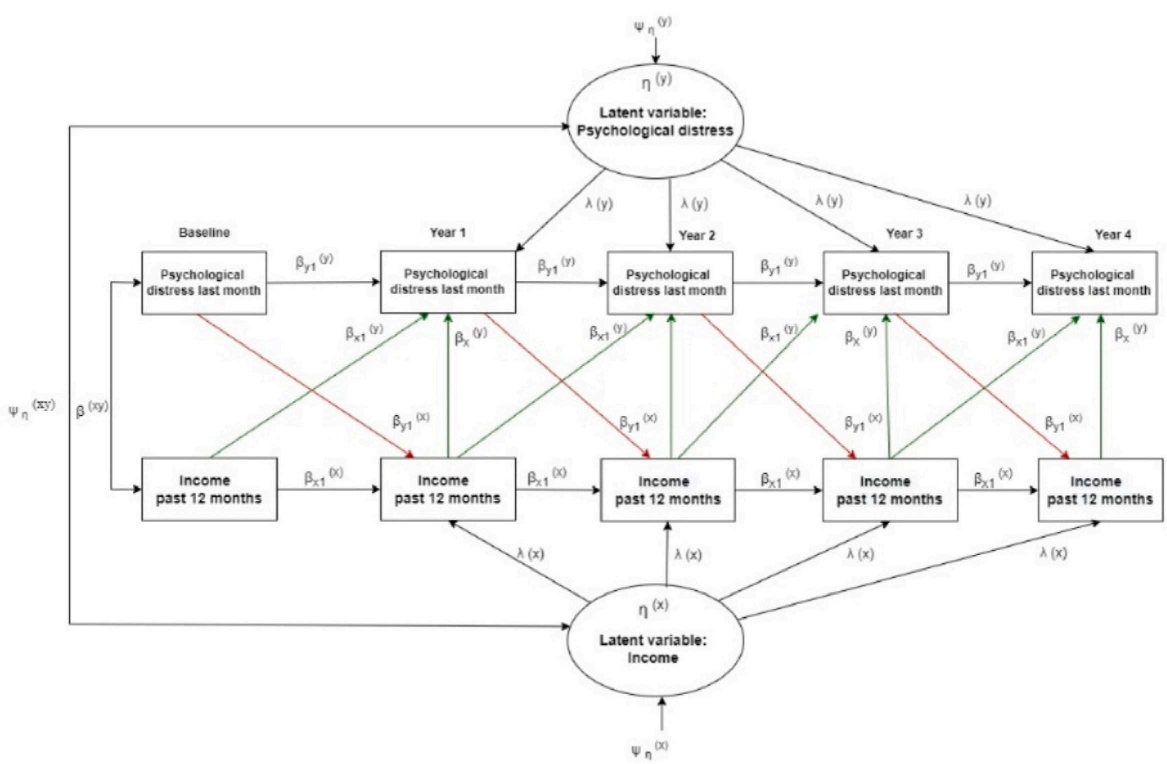

Fig. 1. This figure depicts the specification of the basic FE-CLPM with unit effects in this study, which controls for individual-specific, time-invariant factors over time. For simplicity, we only show variables associated with cross-lagged and auto-regressive effects, and not covariates. $\eta^{(x)}$ and $\eta^{(y)}$ = unit effect (fixed effects for income and psychiatric distress, respectively); $\psi_{\eta}^{(x)}$ and $\psi_{\eta}^{(y)}$ = unit effect variance; λ (x) and λ (y) = factor loadings (which are allowed to vary over time, not constrained); $\beta_{x1}^{(x)}$ and $\beta_{y1}^{(y)}$ = autoregressive effects; $\beta_{x1}^{(y)}$ and $\beta_{y1}^{(x)}$ = cross-lagged effects; $\beta_{x}^{(y)}$ = contemporaneous effect of x on y.

Table 1
Sociodemographic characteristics for working-age adult sample (18–64) at baseline (N = 3103).

	Unweighted N	Unweighted %	Weighted N	Weighted %
Gender				
Male	1246	40.15	1437	46.32
Woman	1857	59.85	1665	53.68
Age: mean (SD)		41.83 (13.52)		40.65 (13.67)
18–25	501	16.15	563	18.15
26–45	625	20.14	727	23.43
46–55	1335	43.02	1217	39.22
56–64	642	20.69	596	19.20
Race/ethnicity				
White non-Hispanic	864	27.84	1009	32.52
Black non-Hispanic	844	27.20	721	23.24
Hispanic	1077	34.71	911	29.37
Asian	144	4.64	375	12.07
Other/multiracial	174	5.61	87	2.80
Immigrant status				
Foreign-born	1060	34.16	1394	44.94
U.S. born	2043	65.84	1709	55.06
Education				
Less than high school	462	14.89	501	16.15
High school grad or GED diploma	645	20.79	624	20.10
Some college	731	23.56	821	26.46
Bachelor's degree or higher	1265	40.77	1157	37.29
Worked last week	1772	57.68	1948	62.79
Number of months worked in last 12		7.44 (5.09)		8.16 (5.26)
Employment status (1)				
Working full-time	1164	46.73	1623	52.29
Working part-time	374	15.01	388	12.49
On leave, laid off	36	1.45	32	1.05
Looking for work	217	8.71	237	7.63
Unable to work	229	9.19	197	6.35
Keeping house	73	2.93	118	3.80
Going to school	88	3.53	139	4.47
Retired	108	4.34	148	4.78
Other	202	8.11	221	7.13
NYC Borough				
Manhattan	750	24.17	715	23.04
Brooklyn	878	28.30	864	27.84
Bronx	700	22.56	603	19.41
Queens	616	19.85	750	24.18
Staten Island	159	5.12	171	5.52
Living with partner	1145	36.90	1407	45.35
Number of children: mean (SD)		0.69 (1.08)		0.72 (1.10)
0	1914	61.68	1884	60.72
1	584	18.82	571	18.39
2	380	12.25	417	13.44
3	144	4.64	139	4.47
4 +	81	2.61	92	2.98

(1)N = 2491 (observed 9 months after baseline).

12-month income reported contemporaneously with distress (past-year earnings or family income); and (b) 12-month income reported a year before data collection on distress. Including income measures with two different temporal lags will allow us to examine how immediate and enduring the effect of income changes may be (Leszczensky & Wolbring, 2019).

Cross-lagged effects are constrained to be the same across all time periods for parsimony and to ease interpretability (Allison et al., 2017). However, we do not constrain auto-regressive effects [$\beta_{x1}{}^{(x)}$ and $\beta_{y1}{}^{(y)}$] to be the same over time and thus allow for these effects to vary and control for the persistence of impulses (Zyphur et al., 2020). Furthermore, we do not constrain the 'factor loadings' of income and psychological distress measures at each timepoint to their respective latent variables [λ (x) and λ (x)]. By doing this, we allow for the possibility that unit effects have time-varying effects over time (Zyphur et al., 2020). This is an important advantage of FE-CLMP over conventional fixed effects, which must assume time-constant effects and thus do not control for unmeasured time-invariant variables when their effects change over time (Allison et al., 2017; Leszczensky & Wolbring, 2019). Allowing time-varying unit effects has two related advantages. First, by leaving the factor loadings for the latent variables [λ (x) and [λ (x)] unconstrained, we relax the assumption of mean stationarity (Bun & Sarafidis, 2015). Second, time-varying unit effect effectively introduces an interaction between unit effects and time [λ_i x η_i] that accounts for unit-specific trends (Zyphur et al., 2020). To test the benefits of this specification we also ran our main models constraining factor loadings. Coefficients for constrained models are slightly stronger, but log likelihood ratio chi square tests indicate that unconstrained models have a superior fit and that introducing time-varying unit effects is more consistent with the data (See Supplemental Material, Tables A.2.1 and A.2.2).

All our models control for contemporaneous and lagged values of two key time-varying factors that can affect both income and mental health:(1) partnership status (dichotomous variable indicating whether the individual lives with a spouse or partner), and (2) number of children (entered as a continuous variable) (McDonald et al., 2022).

To explore differences across sociodemographic groups, we specified additional FE-CLPM models by age group (18–25, 26–55, and 56–64), gender (men, women), educational level (less than a bachelor's degree, and bachelor's degree or higher), and racial/ethnic identification (White non-Hispanic, Black, and Hispanic). Age sub-groups reflect the age of individuals reported at baseline (See Tables 3 and 4). We also specified models with more disaggregated levels of education. Models for those with less than high school education failed to converge when unconstrained unit effects were specified, possibly due to the smaller sample size (n = 462) and additional parameters. We present models for individuals with high school diploma and some college education as Supplementary Material (Table A4).

We estimate confidence intervals via bootstrap method (with 1000 samples) to relax the assumption of normal distribution in our variables (Efron, 1987). To ease interpretability, we present standardized coefficients. We assess the goodness of fit for each model specified by calculating RMSEA, CFI and TLI estimates. We use typical ranges for each estimate to determine good fit (RMSEA <0.06, CFI >0.90 and TLI >0.90) (Hu & Bentler, 1999). All models estimated for our analyses demonstrated acceptable to excellent fit. Fit statistics are presented at the bottom of each table.

3. Results

3.1. Sociodemographic characteristics

Table 1 presents sociodemographic characteristics of the weighted and unweighted sample at baseline. The sample is weighted using data from the 2014–2016 American Community Survey, to make it representative of the 2015 NYC population. Appendix Table A1 summarizes descriptive statistics for psychological distress, individual earnings, and family income-to-needs ratio at baseline.

3.2. Cross-lagged effects

Table 2 presents the standardized cross-lagged coefficients for models with individual earnings and family income. In the first model, we find that changes in individual earnings received in the past 12 months (past-year earnings) have a small but statistically significant negative effect on past-month psychological distress. On average, a one standard deviation decrease in past-year earnings increases recent psychological distress by 0.073 SD (p≤ .001). The direct effect of 12-month earnings reported a year prior is not significant (beta= −0.0006, p= .777). Recent psychological distress also has a small but statistically

Table 2
Standardized coefficients for cross-lagged effects between income types and psychological distress among working-age adults 18–64 (n = 3103).

Model for Individual Earnings and Distress	Cross-lagged coefficients [95% CI]	p-value	Model for Family Income and Distress	Cross-lagged Coefficients [95% CI]	p-value
Psychological distress (t)			Psychological distress (t)		
<- Past-year individual earnings (t)	-.073 [-.101, -.045] ***	.000	*<- Past-year family income (t)*	-.033 [-.052, -.013] **	.005
<- Individual earnings reported a year prior (t – 1)	-.006 [-.040, .024]	.777	*<- Family income reported a year prior (t – 1)*	-.017 [-.036, .003]	.155
Individual earnings reported a year later (t + 1)			Family income reported a year later (t + 1)		
<- Psychological distress at t	-.030 [-.048, -.013] **	.006	*<- Psychological distress at t*	-.026 [-.054, .004]	.147
Model fit statistics			Model fit statistics		
RMSEA	.009		RMSEA	.019	
TLI	.998		TLI	.985	
CFI	.999		CFI	.991	

†p≤.1 *p≤.05; **p≤.01; ***p≤.001.
Psychological distress (t): Measure of global distress based on symptoms experienced in the past 30 days; *Last-year earnings (t):* Earnings the individual received in the last 12 months reported at the same time as their psychological distress measure; *Earnings reported a year prior (t-1):* 12-month earnings reported a year before their psychological distress measure, which refers to earnings the individual received approximately 13-24 months prior to their answers about psychological distress. Earnings reported a year later (t + 1)*:* 12-month earnings the individual reported a year after their psychological distress measure. 95% confidence intervals (CI) estimated via bootstrap method (reps = 1000).

Table 3
Standardized coefficients for cross-lagged effects between income and psychological distress among working-age adults: Models by age & gender.

	18-25 (n = 501)		26-55 (n = 1960)		56–64 (n = 642)		Men (n = 1246)		Women (n = 1857)	
	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value
Psychological distress (t)										
<- Last-year earnings (t)	-.019 [-.082, .032]	.595	-.096 [-.137, -.057] ***	.000	-.060 [-.110, .006] †	.099	-.98 [-.151, -.028] **	.007	-.060 [-.094, -.025] **	.005
<- Earnings reported a year prior (t – 1)	-.003 [-.058, .058]	.936	-.027 [-.069, .015]	.286	.020 [-.042, .077]	.578	-.025 [-.083, .038]	.500	.003 [-.042, .040]	.918
Earnings reported a year later (t + 1)										
<- Psychological distress at t	-.009 [-.090, .067]	.850	-.028 [-.052, -.005] *	.049	-.047 [-.090, -.005] **	.007	-.055 [-.040, .003] †	.057	-.027 [-.048, -.006] *	.040
Model fit statistics										
RMSEA	.029		.001		.015		.000		.013	
TLI	.952		1.00		.996		1.00		.996	
CFI	.972		1.00		.997		1.000		.998	
Psychological distress (t)										
<- Past-year family income (t)	-.059 [-.098, .009] †	.079	-.020 [-.047, .006]	.219	-.034 [-.074.004]	.148	-.031 [-.069, .004]	.165	-.034 [-.056, -.010] *	.018
<- Family income reported a year prior (t – 1)	-.069 [-.115, .004] †	.052	.011 [-.034, .014]	.476	.011 [-.026, .048]	.645	-.017 [-.053, .017]	.432	-.016 [-.039, .010]	.304
Family income reported a year later (t + 1)										
<- Psychological distress at t	-.039 [-.103,.081]	.478	-.020 [-.055, .011]	.326	-.021 [-.095, .040]	.627	.007 [-.045, .050]	.814	-.050 [-.087, -.009] *	.038
Model fit statistics										
RMSEA	.023		.019		.029		.014		.024	
TLI	.957		.986		.981		.991		.977	
CFI	.975		.992		.989		.995		.987	

†p≤.1 *p≤.05; **p≤.01; ***p≤.001.

significant effect on the next 12-month earnings (beta = −0.030, p= .006).

In the second model, we find that past-year family income has a small but statistically significant negative effect on recent psychological distress (beta= −0.033, p= .005). The effect of family income reported a year prior is even smaller and not significant (beta= −0.017, p= .155). Recent psychological distress has a small effect on family income reported a year later, but this effect is also not significant (beta= −0.026, p= .147).

In sum, we find evidence of a bidirectional relationship between earnings and psychological distress, and only of a unidirectional effect of family income on distress. Furthermore, we find that the effect of past-year individual earnings on distress is 2.2 stronger than the effect of past-year family income.

3.3. Sub-group analyses

Cross-lagged effects by age, gender, education, and race/ethnicity. To explore potential heterogeneity of effects, we specified additional models to further examine cross-lagged effects across sociodemographic groups defined by age, gender, levels of education, and racial/ethnic identities.

In the first three columns of Table 3 we present the findings of our model by age groups: 18–25 (young adults), 26–55 (prime working-age) and 56–64 (pre-retirement age). The top panel presents the findings for our models examining cross-lagged effects between earnings and distress; the bottom panel presents coefficients for the effects between family income and distress. Our findings suggest important differences by age. On average, a one standard deviation decrease in past-year

Table 4
Standardized Coefficients for Cross-lagged Effects between Income and Psychological Distress among Working-Age Adults: Models by Levels of Education and Racial/ethnic identities.

	Less than Bachelor's degree (n = 1838)		Bachelor's degreee or higher (n = 1265)		Whites, non-Hispanic (n = 864)		Blacks (n = 844)		Hispanics (n = 1077)	
	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value	Cross-lagged coefficients [95% CI]	p-value
Psychological distress (t)										
<- Last-year earnings (t)	-.077 [-.115, -.040] ***	.001	-.050 [-.084, -.012] *	.027	-.070 [-.122, -.011] *	.042	-.089 [-.135, -.039] **	.003	-.064 [-.115, .004] †	.071
<- Earnings reported a year prior (t – 1)	.002 [-.040, .042]	.941	-.019 [-.062, .026]	.431	.014 [-.049, .071]	.699	.044 [-.009,.093]	.162	-.048 [-.102, .020]	.210
Earnings reported a year later (t + 1)										
<- Psychological distress at t	-.046 [-.073, -.021] **	.004	-.009 [-.036, .017]	.582	-.012 [-.017, .046]	.501	-.014 [-.046, .018]	.478	-.078 [-.108, -.037] ***	.000
Model fit statistics										
RMSEA	.000		.011		.009		.019		.008	
TLI	1.00		.997		.998		.990		.998	
CFI	1.00		.998		.999		.994		.999	
Psychological distress (t)										
<- Past-year family income (t)	-.032 [-.056, -.009] *	.024	-.019 [-.049, .010]	.296	-.003 [-.035, .030]	.861	-.028 [-.067, .007]	.214	-.040 [-.072, -.001] †	.074
<- Family income reported a year prior (t – 1)	.015 [-.039, .008]	.288	-.013 [-.043, .013]	.431	-.014 [-.044, .020]	.487	.009 [-.032, .046]	.719	-.042 [-.076, -.006] *	.049
Family income reported a year later (t + 1)										
<- Psychological distress at t	-.037 [-.078, .013]	.184	-.007 [-.047, .031]	.787	.016 [-.044, .069]	.633	-.006 [-.075, .074]	.903	-.082 [-.136, -.018] *	.021
Model fit statistics										
RMSEA	.016		.021		.007		.019		.023	
TLI	.984		.984		.998		.981		.970	
CFI	.991		.991		.999		.989		.983	

†p≤.1 *p≤.05; **p≤.01; ***p≤.001.

earnings increases recent psychological distress by 0.096 SD (p≤ .001) among prime working-age adults. The effect of past-year earnings on distress for individuals of pre-retirement age (beta= −0.060, p = .099) approaches significance at 0.1, while the effect for young adults (beta= −0.019, p= .595) is noticeably smaller and non-significant. Distress has a statistically small but significant negative effect on next-year earnings for prime working-age (beta= −0.028, p= .049) and pre-retirement age (beta= −0.047, p= .007) individuals; the coefficient for young adults is close to zero and non-significant (beta= −0.009, p= .850). Hence, we find consistent evidence of bidirectional effects between past-year earnings and recent distress for those of prime working-age, weaker evidence for those of pre-retirement age, and no evidence for young adults. We find no evidence of bidirectional effects between family income and distress across age groups, but we do find borderline statistically significant social causation effects of past-year family income (beta= −0.059, p = .079) and family income reported a year prior (beta= −0.069, p = .052) on distress for young adults. We find smaller and non-significant effects among other age groups.

The last two columns in Table 3 present cross-lagged coefficients by gender. In sum, we find evidence of bidirectional effects between past-year earnings and distress for men and women, with the effect of earnings on distress being slightly stronger for men (beta= −0.098, p≤ .007) than women (beta= −0.060, p≤ .005). For family income and distress, we only find evidence of bidirectional effects among women (social causation beta= −0.034, p = .018; social drift beta = −0.050, p = .038).

The first two columns of Table 4 present our findings by levels of education. We find evidence of bidirectional effects between earnings and distress among individuals with less than a bachelor's degree (BA), but not for those with a BA or higher. For the group with education below BA, a one standard deviation decrease in past-year earnings is associated with an 0.077 SD increase in distress (p≤ .001), while an increase in distress is associated with a 0.046 SD decrease in next-year earnings (p= .004). Among people with at least a BA we find a statistically significant unidirectional effect from past-year earnings to distress (beta = −0.050, p = .027), but not from distress to next-year earnings (beta= −0.009, p= .582). We find no bidirectional effects for either educational group in our models for family income and distress. However, we find a small and significant effect of family income on distress for those with less than BA (beta= -.032, p = .024).

The last three columns of Table 4 present cross-lagged coefficients for White non-Hispanics, Blacks, and Hispanics. Although we find significant or borderline significant social causation effects of past-year earnings on distress across all groups, we only find and a significant social drift effect of distress on next-year earnings among Hispanics (beta= −0.078, p≤ .001). Thus, our subgroup analyses only find evidence of bidirectional effects between earnings and distress for Hispanics. The models for family income and distress also show evidence of bidirectional effects for Hispanics, with borderline significant or significant effects of past-year family income (beta= -0.040, p = .074) and family income reported a year prior (beta= −0.042, p = .049) on distress, and distress on next-year family income (beta= −0.082, p = .021). It is noteworthy that the social causation effect of family income is close to zero for Whites (beta= −0.003, p = .861). In fact, most of the social causation effect of family income found in our main models seems to be driven by the effects experienced by Hispanics and Blacks.

4. Discussion

Studies have consistently linked SES and mental health, but whether SES causes mental health problems (social causation), or mental health deterioration causes SES decline (social drift), or both, continues to be an important debate in social sciences and psychiatric epidemiology. Our study reveals new evidence of the reciprocal relationship between income and psychological distress among working-age adults. With an average effect of -0.07 SD, the social causation effect of past-year earnings on distress was found to be remarkably consistent with recent systematic reviews, which find effects of income on mental health ranging between 0.07 and 0.09 SD (McGuire et al., 2022; Ridley et al., 2020; Thomson et al., 2022). A one percentile decrease in past-year earnings is associated on average with a 0.2% increase in current distress (unstandardized coefficient = −0.002). For an individual with annual earnings of $17,000 in 2019, an earnings loss of $10,000 by 2020 would represent a 10-percentile decline and lead on average to a 2% increase in distress. To contextualize this effect, it is important to note that most individuals in our sample (62%) reported scores below 5, the cutoff for moderate distress, while the mean K6 score in the United States population is about 2.8 and the median 2 (Tomitaka et al., 2019). With respect to social drift, we also found that distress had a statistically significant – yet smaller - effect on earnings a year later (−0.03 SD): a ten percent increase in distress leads on average to a decline of 0.11 earnings percentile. While the social causation and social drift effects between earnings and distress are relatively small, these represent average effects in one year. For some individuals, the combined social causation and social drift effects over time may activate a cycle of cumulative socio-economic and mental health decline (Dannefer, 2020). Furthermore, the bidirectional relationship between earnings and distress may operate as a mechanism to deepen economic and mental health inequities. Declines in earnings can increase individuals' likelihood of experiencing material hardship (e.g., inability to meet basic needs or repay debts) and trigger financial stress (Fitch et al., 2011; Heflin & Iceland, 2009). Worsening mental health can lead to loss of productivity (e.g., reduced number of hours worked) (Mall et al., 2015), employment stigma and discrimination (Sharac et al., 2010), loss of employment and income (Ridley et al., 2020), and missed economic opportunities (Taylor, Menachemi, Gilbert, Chaudhary, & Blackburn, 2023).

Our study also finds important differences in the direction and magnitude of effects depending on the income measures examined. Specifically, we only find evidence of a unidirectional, social causation effect from family income to psychological distress, as the effect of recent distress on next-year family income is weak and not statistically significant. This finding is consistent with research indicating that studies using labor market indicators of SES (e.g., wages, employment) are more likely to find evidence of both social causation and social drift effects while studies utilizing non-labor market indicators (e.g., household income, education) are more likely to only find social causation effects (Kröger et al., 2015). An individual's deteriorating mental health may lead to loss of productivity (e.g., non-work, reduced work, lower earnings) but not necessarily to lower income for the entire family unit. Earnings from other family members, other sources of income, and cash transfers in response to decreases in earnings may serve as buffers to losses in individual earnings (Ng & Tan, 2021). Moreover, we find that the effect of past-year family income on distress is weaker than the effect of individual earnings. The standardized coefficient for family income on distress (beta = -0.03) is less than one half the size of the coefficient for earnings, suggesting that earnings have a stronger impact on psychological distress than family income. Decreases in earnings can not only affect the ability to meet basic needs but also diminish one's sense of purpose and personal value (Sage, 2018), while increases in earnings can improve self-esteem and self-efficacy (Bleidorn et al., 2023). Our family income measure (income-to-needs ratio), which includes the income of all relatives in the household as well as government cash and in-kind supports, reflects the extent to which families can meet their basic needs. The experience of distress seems to be more sensitive to changes in one's ability to earn than to changes in the overall income of one's family. Taken together, these findings suggest that individual earnings may play a more important role as a social determinant of mental health than family income.

We also find a noticeable difference in the magnitude of income effects depending on the temporal lag. Across all models, more contemporaneous changes in income - individual earnings and family income in the past year – were stronger predictors of changes in psychological distress than income reported a year prior. Income between one and two years prior did not generally have an effect above and beyond its effect through more recent income, which may suggest that the effect of short-term income declines may be buffered via economic supports provided in response to such declines (Kiely et al., 2015).

Another important finding of our study relates to differences in bidirectional effects across groups by age, education, gender, and racial/ethnic identities.

Across age groups, we find the most consistent evidence of reciprocal effects between earnings and distress among prime working-age adults, followed by those of pre-retirement age. We find no evidence of effects for young adults. These findings are consistent with research suggesting that working-age individuals are most likely to experience the effects of economic stressors on mental health (Breslau et al., 2021), and that income trajectories have strongest effect on mental health at middle-age (Frech & Damaske, 2019). Relative to young adults, prime working-age and pre-retirement age individuals may be more likely to have long-term financial obligations (e.g., children, debts), which may increase their sensitivity to experiencing earnings shocks as changes in financial stress and, in turn, psychological distress. Also, declines in earnings may affect the sense of personal self-worth associated with earnings and lead to stress (e.g., shame, negative social comparison), especially among prime working-age individuals, for whom work is most normative. Overall, we found no evidence of reciprocal effects between family income and distress across age groups. Interestingly, we do find evidence of social causation effects from family income to distress for young adults. Young adults, who are more likely to be students and depend on parental or family income, may experience changes in their own earnings as more normative, while changes in their family income may affect their ability to meet basic needs and hope towards the future (Zimmerman et al., 2021).

We also find differences in social drift effects across age groups. Pre-retirement age individuals seem to experience stronger social drift effects from distress to earnings. In fact, the evidence of social drift effects is stronger as age increases. It is possible that increasing psychological and physical vulnerabilities associated with older age may limit the ability of individuals to protect themselves from the economic impact of distress (Kivimäki et al., 2020).

We also find some heterogeneity of effects by gender. While we observe reciprocal effects between earnings and distress for both men and women (with somewhat stronger effects among men), we only find evidence of reciprocal effects between family income and distress for women. Most notably, changes in the level of distress of women have a small but significant impact on the overall income of the family over the following year, which may reflect the impact that the mental health of women heads of household can have on the income and wellbeing of families (Coles & Cage, 2022).

Our findings also provide evidence that the bidirectional effects between earnings and distress differ by level of education. We only find reciprocal effects for those with less than BA education. Among those with at least a BA, we only find evidence of a unidirectional effect from earnings to distress. We find no evidence of reciprocal effects for family income and distress across education levels. However, we do find a social causation effect of family income on distress for those with less than BA. The evidence about the social causation effects of earnings and family income for those with less than BA is consistent with multiple studies concluding that the effects of income on mental health are stronger among individuals with lower education and lower income, who may have access to fewer resources (e.g., savings, assets) to protect themselves from the impact of income shocks (McGuire et al., 2022; Thomson et al., 2022). It is noteworthy that our coefficients for those with less than BA may conflate substantive differences within that group. Exploratory subgroup analyses by more disaggregated levels of education indicate, for instance, that the social causation effect of earnings for those with a high school education is three times the size of the effect found among those with at least some college education (See Supplemental Material, Table A4).

Racial/ethnic identification also seems to moderate the relationship between income types and distress. Although we find evidence of social causation effects of earnings on distress across all racial/ethnic identities, we only find evidence of bidirectional effects among Hispanics. Most notably, the social drift effect of distress on earnings is only significant among Hispanics and noticeably larger than for non-Hispanic Whites and Blacks (6.5 and 5.5 times, respectively). For the relationship between family income and distress, again, we only find evidence of reciprocal effects among Hispanics. In fact, most of the social causation effect that family income has on distress seems to be driven by the effect among Hispanics and Blacks. The social drift effect of family income for Hispanics is 5 and 14 times larger than for Whites and Blacks, respectively. In the face of psychological distress, Hispanics are much more likely to experience a decline in their earnings and family income a year later. Several factors may contribute to this. In our sample of New York City adults, Hispanics have on average markedly lower earnings, family income and educational attainment relative to non-Hispanic Whites and somewhat lower than Blacks (data available upon request). As a result, Hispanics may have lower access to essential economic resources and mental health supports to cope with periods of declining mental health and to prevent loss of productivity, employment, and income (e.g., job security, paid sick leave, unemployment insurance, health insurance, and mental health treatment) (Ananat & Gassman-Pines, 2023; Bartel, Kim, & Nam, 2019). Our finding of no social drift effect among Blacks is somewhat puzzling given that, although less pronounced than Hispanics, Blacks also experience significant economic and job insecurity (Bartel et al., 2019). It is possible that access to non-economic resources among Blacks (e.g., family support, church affiliation) may serve as buffers preventing or delaying short-run economic declines in the face of distress (Hughes, Kiecolt, & Keith, 2013; Momplaisir, 2018). Further research should further examine potential protective factors for Blacks.

5. Strengths and limitations

This study has several strengths and limitations. Data for this study come from a representative sample of adults in New York City. While racially/ethnically diverse, the relationships found in our sample may be affected by dynamics between income and mental health that are not generalizable to rural contexts or other regions of the United States with different mental health stressors and protective factors (e.g., welfare supports, cultural views on earned income, social supports). Future research should replicate the analytical approaches in this study with nationally representative samples.

It is important to note that the effects examined in this study refer to short-term effects of changes in income on distress, and vice versa. Our study leverages yearly within-person variation in these factors to examine some of the mechanisms through which SES plays a role as a social determinant of mental health (Zyphur et al., 2020). However, SES and mental health are likely to affect each other not only through short-term changes but also through long-run effects of other indicators, such as permanent income, education, neighborhood conditions, and serious mental illness (Shamsollahi, Zyphur, & Ozkok, 2021). The findings of our study should be interpreted in this context. Future studies should examine the long-run and cumulative effects between SES and mental health indicators.

The presence of time-trends underlying two processes being studied (e.g., parallel upward trends in earnings and distress) can threaten causal inference in longitudinal studies, such as in conventional CLPMs. However, our FE-CLPM model specification includes the stronger assumption of time-varying unit effects, which controls for unit-specific trends (Zyphur et al., 2020) (See Model Specification). As robustness checks, we ran four sets of conventional fixed effects models for earnings-distress and family income-distress with and without time-trends. We find significant social causation and social drift effects in all models, and significant time effects in most models. However, the effect of time only changes coefficients slightly, suggesting that any time-trends may not bias our estimates significantly (See Supplemental Material, Table A3.). Our models for earnings may include an additional protection against bias associated with time-trends. Changes in earnings percentiles do not directly represent changes in dollar amounts. They reflect changes in the ranking order of earnings, that is, the relative position of an individual's earnings with respect to the earnings of all others, which may reduce the impact of time-trends in earnings, unless these have significantly heterogenous effects across individuals.

Our model specification and analyses cannot rule out cohort effects. Our finding that reciprocal effects between earnings and distress among prime working-age and pre-retirement individuals is consistent with research suggesting that changes in earnings are most likely to impact the mental health of middle-age adults (Breslau et al., 2021). However, it is possible that differences across cohorts due to varying social expectations across generations could be driving these effects. Future research should examine potential role of cohort effects in the association between income types and distress.

As in other longitudinal studies, our study experienced attrition. About 33% of respondents did not participate in the final wave. We expect that the bias associated with attrition to be minimal since full information maximum likelihood is a powerful estimation method in the presence of missing data (Allison et al., 2017). Furthermore, sensitivity analyses show that estimates are virtually the same when estimated for only those with complete data, those who participated in the last wave, and excluding those who only participated in the baseline survey (Supplemental Material, Table A3).

Monte Carlo simulations of FE-CLPMs have shown that these models require significant amount of data, especially, sufficient within-unit variation and at least three panel waves. Simulations with as little as three waves and 500 observations have been shown to yield unbiased estimates, but samples of that size and number of waves are likely to produce large standard errors, significantly reducing power to detect effects (Leszczensky & Wolbring, 2019). Insufficient power may have affected our ability to detect effects in our sub-group analyses. As such, non-significant coefficients in our subgroup analyses should be interpreted in tandem with effect sizes and sample size. Studies with larger samples should examine heterogeneity of cross-lagged effects between income and distress.

6. Conclusions

Our findings provide empirical support for the reciprocal relationship theory explaining the association between SES and mental health. However, consistent with prior research, our findings suggest that earnings, a labor market indicator, may play a stronger role as social determinant of mental health than family income, a non-labor market indicator. Individual earnings and psychological distress have significant effects on each other over time. Family income has a social causation effect on psychological distress, but the social drift effect of distress on family income is non-significant. Nevertheless, we find important differences across subpopulations. We find the strongest evidence of bidirectional effects between earnings and distress among prime working-age and pre-retirement individuals, those with less than a bachelor's degree, and Hispanics. Although we find no bidirectional effects between family income and distress in our overall sample, a reciprocal dynamic can be observed among women and Hispanics.

Our findings have important research implications. When examining social causation and social drift effects, researchers should consider potential differences in effects across income types, temporal lags, and sub-populations. Future research should investigate reciprocal dynamics utilizing additional measures of SES (e.g., material hardship, multidimensional poverty), examining long-run effects, and including larger samples to identify differences in magnitude and direction of effects across sub-populations.

From a policy perspective, our findings underscore the need to further examine the types of policies that could buffer social causation effects resulting from income shocks and social drift effects associated with worsening mental health. For instance, recent research has found that cash transfers in the United States, such as the Earned Income Tax Credit and Child Tax Credit can improve mental health, especially among those with low education, women, Blacks, and Hispanics (Batra, Jackson, & Hamad, 2023; Cha, Lee, & Tao, 2023; Morgan et al., 2021). However, the potential effect of these policies in buffering the impact of income declines on mental health has not been sufficiently studied. Unemployment insurance generosity has been found to lessen the impact of economic downturns on suicide rates (Cylus, Cylus, Glymour, & Avendano, 2014) and to be generally protective against the negative impact of unemployment on mental health (Renahy et al., 2018). Studies ought to examine the potentially protective effect of unemployment insurance among those with mental health conditions. Part-time sick leave has been shown to increase overall work attendance and reduce long-term disability among those with mental health conditions in Scandinavian countries, but the impact of paid sick leave on labor outcomes for people experiencing mental health declines has not been sufficiently studied in other settings (Viikari-Juntura et al., 2017). Future research should examine these and other policies with the potential of mitigating the deleterious and cumulative effects of reciprocal dynamics between income and mental health, especially among the most vulnerable.

Ethical statement

Ethical approval for the study was obtained from the Columbia University Institutional Review Board.

Funding

Funding for this study was provided by Robin Hood. The funder had no role in the preparation of this manuscript.

CRediT authorship contribution statement

Oscar Jiménez-Solomon: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Garfinkel Irwin:** Writing – review & editing, Supervision, Conceptualization. **Wall Melanie:** Writing – review & editing, Methodology. **Wimer Christopher:** Writing – review & editing, Supervision, Funding acquisition, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2024.101624.

References

Ahrenfeldt, L. J., & Möller, S. (2021). The reciprocal relationship between socioeconomic status and health and the influence of Sex: A European SHARE-analysis based on structural equation modeling. *International Journal of Environmental Research and Public Health, 18*(9). https://doi.org/10.3390/ijerph18095045

Allison, P. D., Williams, R., & Moral-Benito, E. (2017). Maximum likelihood for cross-lagged panel models with fixed effects. *Socius, 3*, Article 2378023117710578. https://doi.org/10.1177/2378023117710578

Anakwenze, U., & Zuberi, D. (2013). Mental health and poverty in the inner city. *Health & Social Work, 38*(3), 147–157. https://doi.org/10.1093/hsw/hlt013

Ananat, E. O., & Gassman-Pines, A. (2023). *Racial differences in unemployment insurance*. Retrieved from https://econofact.org/racial-differences-in-unemployment-insurance .

Aneshensel, C. S. (2009). Toward explaining mental health disparities. *Journal of Health and Social Behavior, 50*(4), 377–394. https://doi.org/10.1177/002214650905000401

Assari, S. (2017). Social determinants of depression: The intersections of race, gender, and socioeconomic status. *Brain Sciences, 7*(12), 156. https://doi.org/10.3390/brainsci7120156

Bartel, A. P., Kim, S., & Nam, J. (2019). Racial and ethnic disparities in access to and use of paid family and medical leave: Evidence from four nationally representative datasets. *Monthly Labor Review, 142*, 1.

Batra, A., Jackson, K., & Hamad, R. (2023). Effects of the 2021 expanded child tax credit on adults' mental health: A quasi-experimental study. *Health Affairs, 42*(1), 74–82. https://doi.org/10.1377/hlthaff.2022.00733

Bentley, R., Baker, E., & Mason, K. (2012). Cumulative exposure to poor housing affordability and its association with mental health in men and women. *Journal of Epidemiology & Community Health, 66*(9), 761. https://doi.org/10.1136/jech-2011-200291

Blanden, J. O., & Gregg, P. (2004). Family income and educational attainment: A review of approahces and evidence for britain. *Oxford Review of Economic Policy, 20*(2), 245–263. https://doi.org/10.1093/oxrep/grh014

Bleidorn, W., Kretzschmar, A., Rauthmann, J. F., Orth, U., Denissen, J. J. A., & Hopwood, C. J. (2023). Self-esteem and income over time. *Psychological Science, 34*(10), 1163–1172. https://doi.org/10.1177/09567976231185129

Breslau, J., Finucane, M. L., Locker, A. R., Baird, M. D., Roth, E. A., & Collins, R. L. (2021). A longitudinal study of psychological distress in the United States before and during the COVID-19 pandemic. *Preventive Medicine, 143*, Article 106362. https://doi.org/10.1016/j.ypmed.2020.106362

Bun, M. J. G., & Sarafidis, V. (2015). Dynamic panel data models. In B. H. Baltagi (Ed.), *The oxford handook of panel data* (pp. 76–110). Oxford: Oxford University Press.

Card, D. (1999). Chapter 30 - the causal effect of education on earnings. In O. C. Ashenfelter, & D. Card (Eds.), *Handbook of labor economics* (Vol. 3, pp. 1801–1863). Elsevier.

Cha, E., Lee, J., & Tao, S. (2023). Impact of the expanded child tax credit and its expiration on adult psychological well-being. *Social Science & Medicine, 332*, Article 116101. https://doi.org/10.1016/j.socscimed.2023.116101

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., … Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *JAMA, 315*(16), 1750–1766. https://doi.org/10.1001/jama.2016.4226

Clayborne, Z. M., Varin, M., & Colman, I. (2019). Systematic review and meta-analysis: Adolescent depression and long-term psychosocial outcomes. *Journal of the American Academy of Child & Adolescent Psychiatry, 58*(1), 72–79. https://doi.org/10.1016/j.jaac.2018.07.896

Coles, D. C., & Cage, J. (2022). Mothers and their children: An exploration of the relationship between maternal mental health and child well-being. *Maternal and Child Health Journal, 26*(5), 1015–1021. https://doi.org/10.1007/s10995-022-03400-x

Collyer, S., Huq, S., Jia, Y., Maury, M., Neckerman, K., Ross, S., et al. (2023). *Poverty tracker data user guide*. Retrieved from New York https://www.povertycenter.columbia.edu/poverty-tracker-data.

Congressional-Research-Service. (2022). *The supplemental poverty measure: Its core concepts, development, and use*. Retrieved from https://crsreports.congress.gov/product/pdf/R/R45031.

Cylus, J., Cylus, J., Glymour, M. M., & Avendano, M. (2014). Do generous unemployment benefit programs reduce suicide rates? A state fixed-effect analysis covering 1968-2008. *American Journal of Epidemiology, 180*(1), 45–52. https://doi.org/10.1093/aje/kwu106

Dannefer, D. (2020). Systemic and reflexive: Foundations of cumulative dis/advantage and life-course processes. *The Journals of Gerontology: Serie Bibliographique, 75*(6), 1249–1263. https://doi.org/10.1093/geronb/gby118

Darin-Mattsson, A., Andel, R., Celeste, R. K., & Kåreholt, I. (2018). Linking financial hardship throughout the life-course with psychological distress in old age: Sensitive period, accumulation of risks, and chain of risks hypotheses. *Social Science & Medicine, 201*, 111–119. https://doi.org/10.1016/j.socscimed.2018.02.012

Demange, P. A., Boomsma, D. I., van Bergen, E., & Nivard, M. G. (2023). Evaluating the causal relationship between educational attainment and mental health. *medRxiv: The Preprint Server for Health Sciences*. https://doi.org/10.1101/2023.01.26.23285029

Dohrenwend, B., & Dohrenwend, B. (1969). *Social status and psychological disorder: A causal inquiry*. John Wiley & Sons.

Efron, B. (1987). Better bootstrap confidence intervals. *Journal of the American Statistical Association, 82*(397), 171–185. https://doi.org/10.1080/01621459.1987.10478410

Elgar, F. J., Pickett, W., Pförtner, T.-K., Gariépy, G., Gordon, D., Georgiades, K., … Melgar-Quiñonez, H. R. (2021). Relative food insecurity, mental health and wellbeing in 160 countries. *Social Science & Medicine, 268*, Article 113556. https://doi.org/10.1016/j.socscimed.2020.113556

Elliott, M. (2001). Gender differences in causes of depression. *Women & Health, 33*(3–4), 183–198. https://doi.org/10.1300/J013v33n03_11

Enders, C., & Bandalos, D. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *8*, 430–457. https://doi.org/10.1207/S15328007SEM0803_5

Ettman, C. K., Cohen, G. H., Abdalla, S. M., & Galea, S. (2020). Do assets explain the relation between race/ethnicity and probable depression in US adults? *PLoS One, 15*(10), Article e0239618. https://doi.org/10.1371/journal.pone.0239618

Fitch, C., Hamilton, S., Bassett, P., & Davey, R. (2011). The relationship between personal debt and mental health: A systematic review. *Mental Health Review Journal, 16*(4), 153–166. https://doi.org/10.1108/13619321111202313

Fox, L. (2017). *The supplemental poverty measure: 2016*. Retrieved from https://www.census.gov/content/dam/Census/library/publications/2017/demo/p60-261.pdf.

Frankham, C., Richardson, T., & Maguire, N. (2020). Psychological factors associated with financial hardship and mental health: A systematic review. *Clinical Psychology Review, 77*, Article 101832. https://doi.org/10.1016/j.cpr.2020.101832

Frech, A., & Damaske, S. (2019). Men's income trajectories and physical and mental health at midlife. *American Journal of Sociology, 124*(5), 1372–1412. https://doi.org/10.1086/702775

Gorgievski, M. J., Bakker, A. B., Schaufeli, W. B., van der Veen, H. B., & Giesen, C. W. M. (2010). Financial problems and psychological distress: Investigating reciprocal effects among business owners. *Journal of Occupational and Organizational Psychology, 83*(2), 513–530. https://doi.org/10.1348/096317909X434032

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods, 20*(1), 102. https://doi.org/10.1037/a0038889

Heflin, C. M., & Iceland, J. (2009). Poverty, material hardship, and depression. *Social Science Quarterly, 90*(5), 1051–1071. https://doi.org/10.1111/j.1540-6237.2009.00645.x

Hu, L.-t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hudson, C. G. (2005). Socioeconomic status and mental illness: Tests of the social causation and selection hypotheses. *American Journal of Orthopsychiatry, 75*(1), 3–18. https://doi.org/10.1037/0002-9432.75.1.3

Hughes, M., Kiecolt, K. J., & Keith, V. M. (2013). How racial identity moderates the impact of financial stress on mental health among african Americans. *Society and Mental Health, 4*(1), 38–54. https://doi.org/10.1177/2156869313509635

Jiménez-Solomon, O., Primrose, R., Moon, I., Wall, M., Galfalvy, H., Méndez-Bustos, P., … Vite, L. (2022). Financial hardship, hope, and life satisfaction among un/underemployed individuals with psychiatric diagnoses: A mediation analysis. *Frontiers in Psychiatry, 13*, Article 867421. https://doi.org/10.3389/fpsyt.2022.867421

Jin, Y., Zhu, D., & He, P. (2020). Social causation or social selection? The longitudinal interrelationship between poverty and depressive symptoms in China. *Social Science & Medicine, 249*, Article 112848. https://doi.org/10.1016/j.socscimed.2020.112848

Johnson, J. G., Cohen, P., Dohrenwend, B. P., Link, B. G., & Brook, J. S. (1999). A longitudinal investigation of social causation and social selection processes involved in the association between socioeconomic status and psychiatric disorders. *108*, 490–499. https://doi.org/10.1037/0021-843X.108.3.490

Kessler, R. C., Green, J. G., Gruber, M. J., Sampson, N. A., Bromet, E., Cuitan, M., … Zaslavsky, A. M. (2010). Screening for serious mental illness in the general population with the K6 screening scale: Results from the WHO world mental health (WMH) survey initiative. *International Journal of Methods in Psychiatric Research, 19* (S1), 4–22. https://doi.org/10.1002/mpr.310

Kiely, K. M., Leach, L. S., Olesen, S. C., & Butterworth, P. (2015). How financial hardship is associated with the onset of mental health problems over time. *Social Psychiatry and Psychiatric Epidemiology, 50*(6), 909–918. https://doi.org/10.1007/s00127-015-1027-0

Kim-Mozeleski, J. E., Poudel, K. C., & Tsoh, J. Y. (2021). Examining reciprocal effects of cigarette smoking, food insecurity, and psychological distress in the U.S. *Journal of Psychoactive Drugs, 53*(2), 177–184. https://doi.org/10.1080/02791072.2020.1845419

Kivimäki, M., Batty, G. D., Pentti, J., Shipley, M. J., Sipilä, P. N., Nyberg, S. T., … Vahtera, J. (2020). Association between socioeconomic status and the development of mental and physical health conditions in adulthood: A multi-cohort study. *The Lancet Public Health, 5*(3), e140–e149. https://doi.org/10.1016/S2468-2667(19)30248-8

Kondirolli, F., & Sunder, N. (2022). Mental health effects of education. *Health Economics, 31*(S2), 22–39. https://doi.org/10.1002/hec.4565

Kröger, H., Pakpahan, E., & Hoffmann, R. (2015). What causes health inequality? A systematic review on the relative importance of social causation and health selection. *The European Journal of Public Health, 25*(6), 951–960. https://doi.org/10.1093/eurpub/ckv111

Leszczensky, L., & Wolbring, T. (2019). How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. *Sociological Methods & Research.* , Article 0049124119882473. https://doi.org/10.1177/0049124119882473

Lund, C., & Cois, A. (2018). Simultaneous social causation and social drift: Longitudinal analysis of depression and poverty in South Africa. *Journal of Affective Disorders, 229*, 396–402. https://doi.org/10.1016/j.jad.2017.12.050

Mall, S., Lund, C., Vilagut, G., Alonso, J., Williams, D. R., & Stein, D. J. (2015). Days out of role due to mental and physical illness in the South African stress and health study. *Social Psychiatry and Psychiatric Epidemiology, 50*, 461–468. https://doi.org/10.1007/s00127-014-0941-x

Mann, J. J., & Rizk, M. M. (2020). A brain-centric model of suicidal behavior. *American Journal of Psychiatry, 177*(10), 902–916. https://doi.org/10.1176/appi.ajp.2020.20081224

McDonald, A. J., Hamilton, H. A., Elton-Marshall, T., Nigatu, Y. T., Jankowicz, D., Bondy, S. J., … Wickens, C. M. (2022). Household composition and anxiety symptoms during the COVID-19 pandemic: A population-based study. *PLoS One, 17* (11). https://doi.org/10.1371/journal.pone.0277243

McGuire, J., Kaiser, C., & Bach-Mortensen, A. M. (2022). A systematic review and meta-analysis of the impact of cash transfers on subjective well-being and mental health in low- and middle-income countries. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-021-01252-z

McKee-Ryan, F., Song, Z., Wanberg, C. R., & Kinicki, A. J. (2005). Psychological and physical well-being during unemployment: A meta-analytic study. *Journal of Applied Psychology, 90*(1), 53.

Momplaisir, H. (2018). *Racial/ethnic heterogeneity, religion, and mental health: Examining the influence of religiosity on african American and afro-caribbean subjective well-being [doctoral dissertation*. Virginia Tech: Virginia Polytech Institute and State University. Retrieved from http://hdl.handle.net/10919/83870.

Moral-Benito, E. (2013). Likelihood-based estimation of dynamic panels with predetermined regressors. *Journal of Business & Economic Statistics, 31*(4), 451–472. https://doi.org/10.1080/07350015.2013.818003

Morgan, E. R., DeCou, C. R., Hill, H. D., Mooney, S. J., Rivara, F. P., & Rowhani-Rahbar, A. (2021). State earned income tax credits and suicidal behavior: A repeated cross-sectional study. *Preventive Medicine, 145*, Article 106403. https://doi.org/10.1016/j.ypmed.2020.106403

Mossakowski, K. N. (2014). *Social causation and social selection*. The Wiley Blackwell Encyclopedia of Health, Illness, Behavior, and Society. https://doi.org/10.1002/9781118410868.wbehibs262

Mund, M., & Nestler, S. (2019). Beyond the Cross-Lagged Panel Model: Next-generation statistical tools for analyzing interdependencies across the life course. *Advances in Life Course Research, 41*, Article 100249. https://doi.org/10.1016/j.alcr.2018.10.002

Muntaner, C., Eaton, W. W., Miech, R., & O'Campo, P. (2004). Socioeconomic position and major mental disorders. *Epidemiologic Reviews, 26*(1), 53–62. https://doi.org/10.1093/epirev/mxh001

Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus user's guide* (8th ed.). Los Angeles, CA: Muthén & Muthén.

Ng, I. Y. H., & Tan, J. Q. (2021). Economic distress and health: A fixed effects analysis of low-income persons in Singapore. *International Journal of Social Welfare, 30*(1), 17–29. https://doi.org/10.1111/ijsw.12426

O'Donnell, A. W., Stuart, J., & O'Donnell, K. J. (2020). The long-term financial and psychological resettlement outcomes of pre-migration trauma and post-settlement difficulties in resettled refugees. *Social Science & Medicine, 262*, Article 113246. https://doi.org/10.1016/j.socscimed.2020.113246

Reiss, F. (2013). Socioeconomic inequalities and mental health problems in children and adolescents: A systematic review. *Social Science & Medicine, 90*, 24–31. https://doi.org/10.1016/j.socscimed.2013.04.026

Renahy, E., Mitchell, C., Molnar, A., Muntaner, C., Ng, E., Ali, F., et al. (2018). Connections between unemployment insurance, poverty and health: A systematic review. *The European Journal of Public Health, 28*(2), 269–275. https://doi.org/10.1093/eurpub/ckx235

Ridley, M., Rao, G., Schilbach, F., & Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science, 370*(6522), Article eaay0214. https://doi.org/10.1126/science.aay0214

Sage, D. (2018). Reversing the negative experience of unemployment: A mediating role for social policies? *Social Policy and Administration, 52*(5), 1043–1059. https://doi.org/10.1111/spol.12333

Shamsollahi, A., Zyphur, M. J., & Ozkok, O. (2021). Long-run effects in dynamic systems: New tools for cross-lagged panel models. *Organizational Research Methods, 25*(3), 435–458. https://doi.org/10.1177/1094428121993228

Sharac, J., McCrone, P., Clement, S., & Thornicroft, G. (2010). The economic impact of mental health stigma and discrimination: A systematic review. *Epidemiologia e Psichiatria Sociale, 19*(3), 223–232. https://doi.org/10.1017/s1121189x00001159

Spivak, S., Cullen, B., Eaton, W. W., Rodriguez, K., & Mojtabai, R. (2019). Financial hardship among individuals with serious mental illness. *Psychiatry Research, 282*, Article 112632. https://doi.org/10.1016/j.psychres.2019.112632

Tamborini, C. R., Kim, C., Sakamoto, A., & Sakamoto, A. (2015). Education and lifetime earnings in the United States. *Demography, 52*(1533–7790), 1383–1407. https://doi.org/10.1007/s13524-015-0407-0 (Electronic)).

Taylor, H. L., Menachemi, N., Gilbert, A., Chaudhary, J., & Blackburn, J. (2023). Economic burden associated with untreated mental illness in Indiana. *JAMA Health Forum, 4*(10), Article e233535. https://doi.org/10.1001/jamahealthforum.2023.3535

Thomson, R. M., Igelström, E., Purba, A. K., Shimonovich, M., Thomson, H., McCartney, G., … Katikireddi, S. V. (2022). How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. *The Lancet Public Health, 7*(6), e515–e528. https://doi.org/10.1016/S2468-2667(22)00058-5

Tomitaka, S., Kawasaki, Y., Ide, K., Akutagawa, M., Ono, Y., & Furukawa, T. A. (2019). Distribution of psychological distress is stable in recent decades and follows an exponential pattern in the US population. *Scientific Reports, 9*(1), Article 11982. https://doi.org/10.1038/s41598-019-47322-1

Tomitaka, S., Kawasaki, Y., Ide, K., Akutagawa, M., Yamada, H., Yutaka, O., et al. (2017). Pattern analysis of total item score and item response of the Kessler Screening Scale for Psychological Distress (K6) in a nationally representative sample of US adults. *PeerJ, 5*, Article e2987. https://doi.org/10.7717/peerj.2987

Townsend, N. W. (2002). *Package deal: Marriage, work and fatherhood in men's lives*. Temple University Press.

Viertiö, S., Kiviruusu, O., Piirtola, M., Kaprio, J., Korhonen, T., Marttunen, M., et al. (2021). Factors contributing to psychological distress in the working population, with a special reference to gender difference. *BMC Public Health, 21*(611), 1–17. https://doi.org/10.1186/s12889-021-10560-y

Viikari-Juntura, E., Virta, L. J., Kausto, J., Autti-Rämö, I., Martimo, K.-P., Laaksonen, M., … Solovieva, S. (2017). Legislative change enabling use of early part-time sick leave enhanced return to work and work participation in Finland. *Scandinavian Journal of Work, Environment & Health, 43*(5), 447–456. https://doi.org/10.5271/sjweh.3664

Williams, Mohammed, S. A., Leavell, J., & Collins, C. (2010). Race, socioeconomic status, and health: Complexities, ongoing challenges, and research opportunities. *Annals of the New York Academy of Sciences, 1186*(1), 69–101. https://doi.org/10.1111/j.1749-6632.2009.05339.x

Zimmerman, A., Garman, E., Avendano-Pabon, M., Araya, R., Evans-Lacko, S., McDaid, D., … Lund, C. (2021). The impact of cash transfers on mental health in children and young people in low-income and middle-income countries: A systematic review and meta-analysis. *BMJ Global Health, 6*(4), Article e004661. https://doi.org/10.1136/bmjgh-2020-004661

Zyphur, M. J., Allison, P. D., Tay, L., Voelkle, M. C., Preacher, K. J., Zhang, Z., … Diener, E. (2020). From data to causes I: Building A general cross-lagged panel model (gclm). *Organizational Research Methods, 23*(4), 651–687. https://doi.org/10.1177/1094428119847278