INEQUALITY IN CONTEXT:

Neighborhood Environments and the Association Among Education and Health

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Abstract

The association among a college degree and health is known to vary, in strength, across subsections of the United States population. Recent literature suggests that educational gradients in health are particularly dependent on contextual environments; higher-level social features, such as state of residence, have indeed been shown to modify how advanced educational credentials matters to well-being. To add resolution to this emerging insight, this study examines how *neighborhood environments*, an especially salient level of geographic organization, impact educational gradients in the US. Using data from the Chicago Community Adult Health Study ($n = 3,105$) and Bayesian multilevel regression models, I examine how educational disparities in self-rated health and depressive symptomatology, between college and non-college degree holders, grow/shrink in response to a neighborhood-provided resource and with exposure to a neighborhood-level health challenge. Findings suggest that how tightly coupled a college degree is with well-being is strongly contingent upon one's immediate external risks, but less so on one's access to neighborhood social resources.

Keywords:

population health; educational health disparities; neighborhood context; Bayesian multilevel models

Introduction

Education is a salient predictor of health, defined broadly, in the United States (US) (Montez and Friedman 2015). US adults with advanced educational credentials—particularly those with a college degree or higher—generally experience longer life-spans and elevated general health status (Hummer and Hernandez 2015); decreased risk of developing various chronic and progressive conditions (Sharp and Gatz 2012; Vargas et. al. 2000); and elevated mental health (Erickson et. al. 2016) than their less highly-educated peers. Educational disparities in health have, alongside educational disparities in welfare more generally, persisted in the US for decades and only become *more* acute with time (Masters 2012; Pew Research Center 2014). Under certain conditions and for some outcomes (e.g., self-rated health; depression) too, this association has been shown to be underpinned by a causal process (Chevalier and Feinstein 2006; Lynch and Von Hippel 2016; Warren 2009). The consistent, intensifying, and sometimes causal role that higher education plays in stratifying US health positions this social-input as an enduring, fundamental point of investigation among population health scientists (Hayward et. al. 2015; Phelan et. al. 2010).

In parsing *educational gradients in health*—i.e., the patterns described above, of more highly educated individuals generally possessing better health—researchers have uncovered an elaborate, interactive structure. A single educational gradient does not generalize across the US population; exactly *how much* one benefits from additional educational attainment is contingent upon the arrangement of their other social attributes (Walsemann et. al. 2013). (Social features like race (Kimbro et. al. 2008), gender (Ross and Mirowsky 2006) and childhood socioeconomic status (Montez and Hayward 2014) have, for instance, been shown to modify the extent to which one's health is improved from attaining a college degree.) Cataloging how education interacts with other dimensions of the social world to produce variable health outcomes adds precision to our understanding of how and why education functions as a determinant of health more broadly; studies that describe heterogeneity in educational gradients, across groups of individuals defined by discrete social traits, foreground recent research efforts as such (Bauldry 2015; Sasson 2016; Montez and Friedman 2015).

Among studies pointed at documenting variable educational gradients across the US, some of the most informative are those that clarify the role of geographic context. Indeed, a small, but expanding, set of work has shown that contextual environments modify how education functions as a determinant of health; how predictive education is of well-being has been shown to vary significantly across US states (Montez et. al. 2017), across census regions (Montez and Berkman 2014), across urban and rural communities (Hayward et. al. 1997) and, more broadly, among European nations with varying welfare-regimes (Cambois et. al. 2016). This burgeoning literature posits, altogether, that contextual settings shift the social and economic consequences of having low-levels of education, and thus the health consequences of not possessing a college degree.

Educational gradients in health have indeed been shown to vary, in pronounced ways, across socially-defined environments. As informative as the literature that has produced this insight has been, there is still room for additional analysis. To add resolution to this emerging framework, research that describes how educational disparities in health vary along an incredibly salient level of geographic-organization—i.e., *the neighborhood*—is needed. Neighborhood environments represent among the most immediate, health-relevant, contextual spaces in which individuals operate, and thus contextual profiles that individuals contend with on a daily basis. Describing how individuals of different levels of education experience the *same* neighborhood spaces is an important next-step in understanding how context comes participates in the association among education and health.

In this paper, to help develop ideas of how educational-attainment and environmental-context interact to generate individual-health, I describe how disparities, in health-status and depressive symptomatology, between college and non-college degree holders vary in response to a neighborhood level resource (i.e., social cohesion) and with exposure to a neighborhood-level health risk (i.e., physical hazards). I use data from the Chicago Community Adult Health Study (2001-2003) (House et. al. 2012) and several Bayesian multilevel regression models, with weakly informative priors (Gelman et. al. 2008), to generate the quantities central to this investigation.

The remainder of the paper is organized as follows: the immediate-next section briefly discusses

neighborhood environments and how they might interact with education to produce variable health risks among their residents. The following sections discuss the data, methods, and analytical plan used in this paper. The final sections present the results of the analysis and offer a discussion that contextualizes them within the broader population health literature.

Background

Neighborhood environments as determinants of health

Neighborhood environments are critical dimensions of space in the US. An individual's neighborhood of residence shapes their immediate access to an assortment of social and institutional resources—e.g., social ties and friendship networks; access to public goods—and contact with a breadth of negative social and environmental risks—e.g., exposure to violence; exposure to toxins (Galster 2012; Sampson 2011).

By organizing individuals' daily experiences, neighborhoods directly organize individuals well-being (Diez Roux and Mair 2010). Indeed, the set of social and institutional goods that neighborhoods offer are typically salubrious; individuals living in neighborhoods dense with public spaces or with well-developed social networks can draw upon these collective resources— frequently and (often) at little (or at least reduced) cost—to help supplement their own physical and emotional wellbeing (Diez Roux 2001). Residing in neighborhoods with elevated levels of negative-exposures is conversely health-damaging, as doing so means sustained contact with health-eroding chronic stressors and environmental toxins (Hajat et. al. 2013). Empirical work demonstrates this idea, of neighborhood contextual environments as critical inputs to health in the US: a mixture of studies have shown that individuals who reside in more resource-dense, less-hazardous neighborhoods display elevated general health status (Mode et. al. 2016); fewer chronic and progressive conditions (Mujahid et. al. 2008; Clarke et. al. 2015); and elevated emotional well-being (Latkin and Curry 2003) compared to residents of high-hazard and/or low resource spaces.

Neighborhoods' potential role in shaping educational health gradients

Neighborhood environments, through their allocation of immediate hazards and goods, may be implicit in the association among education and well-being. That is, education is theorized to participate in health by offering individuals a broad collection of salubrious, individual-level resources (Phelan et. al. 2010). The additional income, steady employment, developed personal networks, elevated cognitive functioning and increased feelings of control over one's life that typically accompany advanced educational attainment form a fairly comprehensive "health-toolkit," which can be used to ward off multiple, external health challenges (Cutler and Lleras-Muney 2006; Mirowsky and Ross 2003). If education indeed protects health by offering personal resources that *guard* against the effects of health damaging exposures, then how—and how much—education matters for health may be inextricably linked to social and physical environments that individuals contend with, as well as the alternative, collective resources available to them.

Empirical work, which clarifies how higher-order geographies influence educational gradients, align with this idea. Montez et. al. (2017), for instance, recently demonstrated that educational gradients in disability vary among US states. States where low educational attainment was more tightly coupled with worse material conditions—e.g., in higher poverty rates—displayed wider gaps in disability rates among their low-educated and high-educated populations than did states with less severe inequalities in conditions. Montez et. al. (2017) posited that, through policies and practices that shift the social and economic safety nets available to their residents, states shift how much individuals must rely on their education—and the personal resources that accompany it—to protect their health (Montez et. al. 2017). Similar conclusions are drawn from analyses preformed on regions, urban-rural communities and across nation-states (Cambois et. al. 2016; Hayward et. al. 1997; Montez and Berkman 2014).

Like states and other geographies, neighborhood environments may shift how reliant individuals are on their own education to protect their health. Indeed, in neighborhood spaces dense with high-quality resources, the material consequences of not possessing advanced educational credentials may be trivial; individuals in these spaces may be able to rely on neighborhood-level, collective social and institutional goods to effectively supplement well-being, regardless of their own personal circumstances. Put differently, educational gradients may be relatively shal-

low in neighborhood environments with many neighborhood-level resources, as these alternative, contextual-level goods can be used as effective “stand-ins” for the healthful resources that a college degree would otherwise provide. The interaction among context and gradients may be particularly profound at the neighborhood-level, given that the resources propagated at this level of spatial-organization represent goods that are accessed relatively immediately and interacted with daily.

In the same vein, educational disparities in health may become exacerbated in neighborhood spaces with elevated levels of risks. As Montez et. al. (2017) argue in their exploration of states, *high education may provide a personal firewall to suboptimal context*. Individuals with advanced education may be able to use the resources that accompany their credentials to effectively resist the otherwise health-damaging exposures of more marginalized neighborhood spaces. Lacking these personal, education-borne resources, individuals with lower levels of educational attainment may be more susceptible to the ill-effects of neighborhood propagated health challenges. Again, because of the immediacy of neighborhoods to the individual, the interaction among context, education and personal welfare may be particularly strong at the residential level; in neighborhood environments where daily exposure to health-related challenges are high, education may indeed be an essential means of maintaining good health.

Current Study

Neighborhood environments may indeed, through their distribution of external risks and goods, participate in educational health disparities the US. Given this potentially joint, potentially profound, multilevel association, the present study examines how educational gradients in health fluctuate among neighborhood spaces defined by different characteristics.

In the current study, I describe if the strength of the association among a college degree and physical and mental health varies among neighborhoods with different levels of *neighborhood social cohesion*—a neighborhood-propagated resource—and *neighborhood physicals hazards*—a neighborhood propagated risk. Social cohesion broadly represents the level of social connectedness of a

neighborhood space (e.g., the willingness of residents to work together to solve problems), while physical hazards represents the level of harmful environmental exposures within a space (e.g., noise pollution or air pollution). Both neighborhood social cohesion and physical hazards have been shown to share important, significant associations with individual health (e.g., Ahern and Galea 2011; Beutel et. al. 2016; Hajat et. al. 2016) and are thus chosen as points of comparison for this analysis.

Drawing on the insights developed in analyses of higher-order geographies, I predict that disparities in health among college and non-college educated individuals will be most pronounced in spaces defined by high levels of hazards. (High-educated individuals in high-hazard areas should be able to leverage their education to ward-off external health-challenges better than their less-educated counterparts.) Among neighborhoods with varying levels of cohesion, I expect for educational disparities to be shallowest in spaces defined by high levels of social support. (With strong, external, salubrious social resources available to individuals, I expect for one's personal level of educational attainment to be less essential for maintaining their good health.)

Data

The Chicago Community Adult Health Study

Data for this project come from the Chicago Community Adult Health Study (CCAHS) (House et. al. 2012). The CCAHS is comprised of a cross-sectional sample of 3,105 individuals, all over the age of 18, living in Chicago between 2001 and 2003. Interviewers collected information about each respondent's current social, economic, and demographic circumstances. In addition to collecting characteristics of individual respondents, researchers recorded detailed information on the 343 neighborhood-spaces that individuals inhabited. In these data, "neighborhoods" are defined as subsets of census-tracts that are geographically contiguous and socially and culturally similar. (Please see House et. al. (2012) and Sampson et. al. (1999) for further details on how these neighborhoods spaces are defined.) Note that the 343 neighborhood-clusters in the data represent the *census* of neighborhood-clusters in the city of Chicago.

Measures

The focal individual-level predictor (A), *educational attainment*, is defined around whether a respondent held a college degree at the time of their interview. Individuals who answered *yes* to the question, *do you have a bachelor's degree from a four year college?* are coded as $A = 1$. Individuals who answered *no* are coded as $A = 0$. A college degree is chosen as the focal comparison point given that particularly substantial inequalities, health and otherwise, exists among individuals split across this level of educational attainment (Bauldry 2014; Pew Research Center 2014).

The first health response (Y_1)—*self-rated health*—is defined around a respondent's answer to the question, *all in all, would you say that your health is generally excellent, very good, good, fair, or poor?* Like many other researchers who use this measure (e.g., Braveman and Gottlieb 2014), I group adjacent categories to represent broad regions of health: *excellent/very good health vs other* and *fair/poor vs. other*. I choose this outcome (1) given its strong and consistent correlation with a spectrum of health measures that vary with education (e.g., mortality; recurring health problems; physical tiredness; stress; underlying biomarkers) (Bauldry 2014; Idler and Benyamini 1997; Jylha et. al. 2006; Jylha 2009); and (2) because it has been shown to share a causal relationship with college completion (e.g., Lynch and von Hippel 2016). (Note that because results for *excellent/very good health vs other* and *fair/poor health vs. other* lead to the same substitutive conclusions, I only present results for the former in this paper. Note also that I use *excellent/very good health* and *superlative health* interchangeably from here on.)

The second response (Y_2)—*depressive symptomatology*—is measured using the Center for Epidemiologic Studies Depression Scale (CES-D) (Radloff 1977). The 11-item version of this scale, used in this analysis, asked respondents to assess the frequency, over the last week, in which they felt: *depressed; like everything they did was an effort; that their sleep was restless; that they were happy; lonely; that people were unfriendly; that they enjoyed life; that their appetite was poor; sad; that people disliked them; and that they could not get going* (Kohout et. al. 1993). Response to each item ranged from *never* (0) to *most of the time* (3). Responses were summed to create an overall measure of depressive symptoms; higher scores represent more depressive symptoms. I chose this outcome to

represent mental well-being given its pronounced association with both neighborhood contextual environments and college degree attainment (Bauldry 2015; Latkin and Curry 2003). (Note that, from here on, I will refer to *depression* and *depressive symptomatology* interchangeably.)

Neighborhood physical hazards (Z_1), the first of our neighborhood-level features of interest, is defined using a scale-measure in CCAHS. In the CCAHS questionnaire, each individual was asked a series of questions related to the environmental risks within their neighborhood-cluster; these include: (1) *Some neighborhoods have problems with air quality because of things like exhaust from cars, trucks, and buses; smoke from nearby industrial areas; or dust and dirt from trash or construction. How would you rate the quality of the air in this neighborhood?*; (2) *How dangerous do you think traffic is in your neighborhood either to people driving in cars or walking on the street?*; and (3) *Some neighborhoods are noisier places to live than others. Noise can come from people living nearby, people walking or hanging out on the street, traffic, or construction. How noisy would you say your neighborhood is?*. Using these responses in conjunction with a multilevel Empirical-Bayes technique, CCAHS estimated a neighborhood-level physical hazard score for each neighborhood cluster. (Please see the CCAHS documentation (House et. al. 2012) for additional information on the estimation technique used to construct this measure.) Higher scores on this scale indicate more physically hazardous neighborhoods. Hazard scores range from approximately 2.1 to 3.03.

The second of our neighborhood-level features, *neighborhood social cohesion* (Z_2), is defined using a scale-measure as well. CCAHS respondents were asked to assess the degree to which: (1) *their neighborhood is close knit*; (2) *people in [their] neighborhood are willing to help their neighbors*; (3) *people in [their] get along with each other*; (4) *people in [their] neighborhood can be trusted*; and (5) *people in [their] neighborhood shares the same values*. A multilevel Empirical-Bayes technique was, again, used to combine responses and estimate a neighborhood-level score. Neighborhoods with higher scores on this scale represent neighborhoods with higher levels of cohesion and support. Social cohesion scores range from 2.7 to 3.45.

Additional individual-level, demographic measures are included as controls (X). These include a measure of one's interviewer-observed gender (1 if observed as female; 0 if observed as male);

one's self-reported race/ethnicity (1 if Hispanic/Latinx; 2 if White; 3 if Black; 4 if other); one's age (in log-years); one's immigrant generation (1 if first generation; 2 if second generation; 3 if third or higher); one's parental education (1 if has a college degree; 0 otherwise); a indicator for missing parent education (approximately 10-percent of the sample); and an indicator of if one was born in the South (1 is yes; 0 if otherwise).

Methods

To describe how educational gradients vary across neighborhoods, I estimate a series of Bayesian multilevel regression models for each health outcome and each neighborhood trait. In a first model (Model 1), the health outcome of interest (Y_1 or Y_2) is regressed on college degree status (A), a neighborhood characteristic of interest (either Z_1 or Z_2), the vector of controls described above ($\mathbf{X}$) and a random intercept for each neighborhood cluster. In a second fit (Model 2), the same model is specified, save for that an interaction between the neighborhood trait under investigation and college degree status is specified as well. (This interaction allows for the estimated effect of a college degree to vary along a neighborhood measure.) Logistic and negative binomial models are used for fits of self-rated health and of depression, respectively.

I draw several inferences from the models described above. To assess whether an interaction among educational attainment and a neighborhood trait is supported by the data, I use approximate leave-one-out cross-validation tests (LOOIC) (Vehtari et. al. 2017). If the association among a college degree and health does indeed depend on a neighborhood trait, than specifying this interaction (as in Model 2) should yield predictive accuracy at or beyond the precision of a model that does not allow for these features to interact (as is the case in Model 1) (Gelman and Hill 2008).

To display the substantive implications of the models, I draw from the posteriors of the interactive fits. That is, from Model 2, I calculate an expected value—either a probability of being in superlative health or predicted CES-D score—for both college degree holders and non-college degree holders, across the observed range of each neighborhood trait, holding all other features constant at their means/modes—i.e., $Y(a, z) = E[Y|A = 1, Z = z, \mathbf{C} = \mathbf{c}]$ and $Y(a', z) =$

$E[Y|A = 0, Z = z, C = c]$, respectively, for varying values of Z . Estimates of the difference between these two predictions, which quantifies the magnitude of health disparity among the two educational groups across neighborhood spaces, are calculate from draws of the model posterior as well—i.e., $E[Y(a, z) - Y(a', z)]$ for varying levels of Z .

Bayesian models with weakly informative priors are chosen for this analysis as they help regularize estimates—e.g., prevent single, small-sample size neighborhoods from having over-sized influence on model results—and stabilize computation (Gelman et. al. 2008). Bayesian multilevel models also have the advantage of producing credible intervals that accurately incorporate uncertainty produced at all levels of the model (Fox and Weisberg 2011). Models are fit using the `rstanarm` package (Stan Development Team 2016) in the R statistical programming language (R Core Team 2018). Priors are set to their default values in `rstanarm`, which have been show to aid computation and regularization across a (very) wide-range of scenarios. (The intercept prior is normal with mean 0 and standard deviation 10 (after centering); the coefficients on the predictors have normal priors as well, with mean 0 and standard deviation 2.5. All components of the prior covariance matrix associated with group-specific terms are set to 1. Please see the `rstanarm` documentation (Stan Development Team 2016) for more information.

Results

Table 1: CCAHS sample descriptives ($n = 3,105$)

feature	mean	sd
age	42.5	16.5
generation	2.4	0.85
from south	0.15	-
parent education	0.16	-
has college degree	0.23	-
female	0.60	-
black	0.39	-
latinx	0.25	-
white	0.32	-
superlative health	0.50	-
depression score	9.48	6.32

To aid interpretation, Table 1 offers a summary of the individuals that comprise the CCAHS sam-

ple population. Among the $n = 3,105$ respondents, $n = 724$ have college degrees and $n = 2,381$ do not. 60% of the sample—approximately 1,870 respondents—are interpreted as *female*, while the rest are coded as *male*. Race is distributed fairly uniformly, with 26% of the sample identifying as *Hispanic/Latinx*, 32% as *White*; 39% as *Black*, and 3% as another race/ethnicity. The median age is 40 years old—with the 25th and 75th quantiles being 29 years and 53 years old, respectively—and the majority of individuals (approximately 63% of the sample) are classified as at least third-generation immigrants. Approximately half of the respondents reported being in excellent/very good health and the average CES-D score is approximately 9.5.

To further describe the sample, Figure 1 plots summaries of the neighborhood clusters in the data.

Fig. 1: Summaries of neighborhood clusters. *Top:* count of neighborhoods with x number of college educated individuals and y number of non-college educated individuals. The light gray line represents a smoothed relationship among the two counts. *Bottom:* distribution of neighborhood hazard and social cohesion scales among all individuals in the sample. Green densities represent score distributions among college educated individuals, while blue densities represent distributions among non-college educated individuals.

The top row of Figure 1 shows that the 724 individuals with college degrees and 2,381 individuals without college degrees are spread fairly well across the 343 neighborhoods in the data. While an expected, slightly negative relationship exists among the two counts—in that as the number of college educated individuals increases in a neighborhood, the number of non-college educated individuals decreases—many neighborhood clusters contain a mixture of individuals at different levels of personal educational attainment. On average, each neighborhood contains 9 respondents, 2 of who hold a college degree and 7 of who do not. The smallest neighborhood cluster contained one respondent, while the largest contained 21.

The bottom row of Figure 1 plots the observed relationship among neighborhood hazards, neighborhood social cohesion, and educational attainment. This display shows that both college and non-college educated individuals experience a range of neighborhood conditions. On average, college educated individuals reside in neighborhoods with hazard scores of 2.54 and social cohesion scores of 3.09. Hazard scores are somewhat higher among non-college educated individuals (≈ 2.65) while cohesion scores are lower (≈ 3.03). Note that, despite the improved neighborhood conditions among the college educated sample-population on average, education is not *deterministic* of neighborhood risk/quality; individuals with and without college degrees are spread into various neighborhood contexts in these data.

As a final point of description, education and both neighborhood features of interest share independent association with health in these data. The proportion of college degree holders in superlative self-rated health is 0.25 points higher than the portion of non-college degree holders at the same level of health. Likewise, the average CES-D score is around 1.8 points lower among college educated individuals than among their peers. The observed probability of excellent/very good health shrinks from approximately 0.60 among individuals in the least hazardous neighborhoods to 0.43 in the most hazardous neighborhoods, while average depression scores increase from 8.9 to 10.5. Neighborhood cohesion is similarly informative for health, with the observed probability of superlative health growing from 0.63 to 0.83 from the least to most cohesive neighborhoods and depression scores shrinking from 12.8 to 6.5 across the same range.

Next, to assess whether education and neighborhood environments *interact* to affect individual health, I display results from the models described above. Figures 2 and 3 below plot the model predicted results for neighborhood-hazards.

Fig. 2: Predicted probability of excellent/very good health across varying levels of education and neighborhood hazards. 75% and 90% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.

Fig. 3: Predicted CES-D score across varying levels of education and neighborhood hazards. 75% and 90% credible intervals are marked for the difference in predicted scores across education levels.

Figure 2 show that a pronounced interactive association exists among educational attainment, neighborhood hazards, and self-rated health. Allowing the size of education's association with self-rated health to depend on neighborhood hazards indeed yields a more accurate model, as measured by LOOIC, than one that does not. Predictive plots clarify this interaction's weight; in neighborhoods where exposure to physical hazards are low, the predicted difference in the probability of reporting excellent/very-good health between college and non-college educated individuals is also low. (Among the least hazardous neighborhood environments, the difference in the probability of superlative health between the two educational groups is only 8-percentage points). Educational health disparities grows wider with increasing neighborhood hazards, such that college educated individuals are nearly 33-percentage points more likely to report superlative self-rated than their less educated peers in the most hazardous of neighborhoods environments. Note that the growth in educational disparities that accompanies increasing neighborhood hazards is entirely a product of changes among non-college educated individuals. Individuals with a college degree are estimated to achieve the same level of self-rated health *regardless* of their level of exposure to neighborhood hazards; the health of non-college educated individuals instead drops precipitously with increased exposure to detrimental neighborhood conditions.

Figure 3 displays similar patterns of environmental variation in educational disparities in depression. Allowing an interaction among education and environmental hazards yields approximately the same predictive accuracy as a model that does not. Predictive plots show that while living in a more hazardous space is detrimental the mental well-being of both college and non-college educated individuals, doing so is more damaging to the health of those without a college degree. Indeed, among neighborhoods defined by low levels of physical hazards, the predicted difference in CES-D score among college and non-college educated individuals is about 0.75 points and indistinguishable from 0. As hazards grow, so do educational disparities; in the most hazardous neighborhood spaces, college educated individuals have average depression scores that are 2.5 points lower than adults without a college degree. Again, results here point to college educated individuals being better able to resist the damaging effects of residing in a physically hazardous space.

Next, Figures 4 and 5 display model results for neighborhood social cohesion.

Fig. 4: Predicted probability of excellent/very good health across varying levels of education and neighborhood social cohesion. 75% and 90% credible intervals are marked for the difference in predicted probabilities of self-rated health across education levels.

Fig. 5: Predicted CES-D score across varying levels of education and neighborhood social cohesion. 75% and 90% credible intervals are marked for the difference in predicted scores across education levels.

Compared to neighborhood physical hazards, neighborhood social cohesion appears to participate much less forcefully in educational disparities in welfare. While a model that allows for education's effect to depend on neighborhood social cohesion is as precise as a model that smooths over this nuance, the substantive difference among the two models is negligible. Indeed, as displayed in Figure 4, the predicted difference in self-rated among college and non-college educated individuals remains relatively constant, even when drawing from a model that allows said features to interact; college educated adults living in low social-cohesion spaces and those living in high social-cohesion spaces experience about the same health-advantage over their less highly-educated peers (an approximately 22-percentage point and 18-percentage point advantage, respectively). Note that this consistency in disparities across spaces is a product of stable changes in health for both groups as a function of neighborhood social cohesion. That is, both college and non-college educated individuals in the sample population benefit, at approximately the same rate, from living in spaces with more well-developed, high-quality social resources. This neighborhood feature consequentially has little to no impact on educational disparities in generalized well-being.

Results for the association among neighborhood social cohesion, personal educational attainment, and depression read similarly to those for self-rated health. In this case, forcing a model that includes an interaction among college completion status and cohesion produces a fit that preforms marginally worse than one that excludes this term. Examining the interaction through draws of the posterior indeed clarifies this behavior. Figure 5 shows that both college and non-college degree holders receive pronounced, but approximately equal mental health benefits from residing in neighborhoods with increasing levels of collective social support. In environments defined by low-levels of social cohesion, college educated individuals have CES-D scores that are approximately 1.7 points lower, on average, than CES-D scores non-college educated individuals. The size of this disparity remains fairly consistent across the range of neighborhood social cohesion, with predicted depression scores among college degree holders being about 1.4 points lower than their less-educated peers in the most tightly-knit communities. Again, an interaction among college degree status, neighborhood level social cohesion, and health does not describe these data; the mental well-being of college and non-college educated individuals appears to be equally re-

sponsive to their neighborhood's overall level of cohesion.

Conclusions

Using data from the Chicago Community Adult Health Study and Bayesian multilevel regression models, this study describes how neighborhood contextual environments come to bear on educational gradients in health. Like authors who have examined higher-order spatial contexts, I find that neighborhood environments alter how tightly coupled holding a college degree is with physical and mental well-being.

As initially predicted, I find that educational gradients in health are quite sensitive to neighborhood propagated risks. In neighborhood-environments defined by low-levels of physical hazards, self-rated health and depression differences among college and non-college educated individuals are minimal. In contrast, in environments where exposure to damaging external conditions are high, educational disparities swell—by nearly a factor of 3 for self-rated health and 2.5 for depression—because the health of non-college educated individuals degrades substantially within such environments. This result aligns with Montez et. al.'s (2017) assertion that education acts as a buffer against suboptimal context; indeed, I find evidence that aligns with the idea that individuals with college degrees are able to leverage their credentials to protect against health-damaging exposures that their neighborhoods place upon them. These results show that not only does education wall against the hazardous effects of higher order, quite distal social features, like policies organized around states or regions, but also against external risks propagated at an immediate, everyday, local level.

Findings for neighborhood social cohesion run counter to initial expectations, however. Both college and non-college educated individuals appear to benefit to the same degree from living in neighborhoods with more well-developed, tightly-knit social networks. Educational disparities in physical and mental health indeed remain constant across environments with varying levels of cohesion. As an important aside, note a finding from a prior study on neighborhood environments. As part of a larger project, Browning and Cagney (2002) found some evidence to suggest

that educational disparities in well-being were at their *largest* in spaces defined by high levels of collective efficacy—a positive, neighborhood-level social-resource. Conceptual reasoning for this finding is somewhat unexplored and runs counter to both the conceptualization motivated by more recent studies of how context bears on educational health disparities, as well as the findings of this paper. Taken altogether, these contrasting works suggests that the relationship among neighborhood social-resources and educational health disparities is quite complex, perhaps multifaceted and deserves further empirical and theoretic attention from population health scientists.

In all, this study highlights education as a fundamental cause of disease (Phelan et. al. 2010) and frames a potentially important narrative for how education stratifies health among the US population. That is, the well-being of less highly educated individuals appears to be dependent, on the whole, on their immediate, surrounding environments; both the negative consequences of living in risky environmental spaces and positive effects of residing in socially-rich environments loom large in the physical and emotional well-being of adults without a college degree. More highly-educated individuals, on the other hand, appear able to simultaneously engage with neighborhood spaces when doing so is good for their health and build barriers between themselves and their environments when engaging with said spaces would be health-degrading. These patterns suggest that education's effect on health may be explicitly due to the nuanced control that this social input allows one to exert over their surrounding environment. Indeed, results suggest that education allows individuals to engage flexibly and optimally with their contextual environments in ways that preserve and promote health. (Empirical studies that formally test how neighborhood environments act as *mechanisms* of education's health effect may prove insightful for fleshing this idea out further (Archya et. al. 2017).) If educational inequalities in health are largely underpinned by differential susceptibility to environmental exposures, than efforts that target said contextual exposures may be key for reducing these socioeconomic disparities in health. Studies that examine how other neighborhood-organized features shift educational inequalities would add additional nuance to this perspective; documenting what types of negative environments educational credentials help buffer against could add considerable depth to our understanding of the process that underlies the relationship among education and health.

More broadly, this study adds weight to a burgeoning ensemble of voices, from across the population sciences, that position health as *inherently multilevel* (e.g., Diez Roux 2008; Hayward et. al. 2015; Hicken et. al. 2018; Montez and Friedman 2015; Montez et. al. 2017). Indeed, results for physical hazards empirically illustrate how individual health can be constituted at multiple, interlocking levels of social organization. While both personal-level education and shared physical environments were observed as having additive effects on health, a strong, multiplicative relationship existed among the two, such that interpreting one without the other would leave us with an incomplete understanding of how either functions as a social determinant of health. By extension, this result implies that health disparities among individuals are generated at multiple levels of social resolution, simultaneously, as well. Both empirical and theoretical efforts that clarify how the personal and contextual coalesce may, as this study shows, be key for understanding how health manifest among members of any given population. Fleshing out our descriptions of social-health processes with studies that recognize this idea empirically may prove invaluable for efforts to better identify, and thus address, the origins of population health inequalities.

As a closing point, note that this study is certainly not without limitations—and thus opportunities for future work. CCAHS, while rich along many dimensions, is limited in *pretreatment* (i.e., *pre-educational attainment*) *confounders*. How respondents came their current level of educational attainment and their current health is likely intertwined and largely unobserved in these data. Without better control over these confounding features, results should *only* be interpreted as associations and not as causal relationships. Future research should utilize in-progress data collection efforts, that better record confounding processes across the life-course (e.g., *High School and Beyond: Midlife Follow Up* (Warren et. al. 2017)), to assess results under stricter causal assumptions. Likewise, efforts that take advantage of in-development approaches for handling post-treatment confounding within multilevel settings, while avoiding post-treatment bias, would help move efforts closer to identifying the causal processes that underly these findings (Acharya et. al. 2018; Gelman and Hill 2008; Ratkovic and Tingley 2017). Moreover, although self-rated health is informative, in that it is a distinct dimension of well-being and powerful associate of many other outcomes (Jylha et. al. 2006; Jylha 2009), it is a somewhat coarse assessment of one's physical health. The joint influence of education and neighborhoods should be examined on other physical

health outcomes for additional perspective on the matter. Additional measures of hazardous and social resources should similarly be examined for more insight. Finally, additional research that examines how well these patterns generalize to individuals situated in other cities should be pursued for completeness.

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