Nat Hum Behav. Author manuscript; available in PMC 2020 July 20.

Published in final edited form as:
Nat Hum Behav. 2020 March ; 4(3): 255–264. doi:10.1038/s41562-019-0810-4.

Clustering of health, crime and social-welfare inequality in 4 million citizens from 2 nations

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Abstract

Health and social scientists have documented the hospital revolving-door problem, the concentration of crime, and long-term welfare-dependence. Have these distinct fields identified the same citizens? Using administrative databases linked to 1.7-million New Zealanders, we quantified and monetized inequality in distributions of health and social problems and tested whether they aggregate within individuals. Marked inequality was observed: Gini coefficients equaled 0.96 for criminal-convictions, 0.91 for public-hospital-nights, 0.86 for welfare-benefits, 0.74 for prescription-drug-fills, and 0.54 for injury-insurance-claims. Marked aggregation was uncovered: a small population segment accounted for a disproportionate share of use-events and

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Data availability: The NZIDI and Danish register data cannot be shared by the authors. Researchers who wish to use the NZIDI data must submit an application through Statistics New Zealand. Researchers who wish to use the Danish register data must request permission through the Danish Data Protection Agency. The Dunedin Study data are not publicly available as informed consent and ethical approval for public data-sharing were not obtained from participants. The data are available on request by qualified scientists. Requests require a concept paper describing the purpose of data access, ethical approval at the applicant's institution, and provision for secure data access. We offer secure access on the Duke University, Otago University, and King's College London campuses.

Code availability: Custom code that supports the findings of this study in the New Zealand Integrated Data Infrastructure is provided in the Supplementary Information. Custom code that supports the findings of this study in the Danish nationwide registers and the Dunedin Longitudinal Study is available from the corresponding author upon request.

Author contributions: LSR, AC, BJM, and TEM designed research; LSR, SHA, SH, RP, SR, AC, BJM, and TEM performed research; LSR, SD, SHA, RMH, and BJM analyzed data; and LSR, AC, and TEM wrote the paper. All authors reviewed drafts, provided critical feedback, and approved the final manuscript.

Competing interests: The authors declare no competing interests.

costs across multiple sectors. Findings replicated in 2.3-million Danes. We then integrated the New Zealand databases with the four-decade-long Dunedin Study. The high-need/high-cost population segment experienced early-life factors that reduce workforce-readiness, including low education and poor mental-health. In midlife they reported low life-satisfaction. Investing in young people's education/training potential could reduce health and social inequalities and enhance population wellbeing.

Clustering of health, crime and social-welfare inequality in 4 million citizens from 2 nations

We live in an unequal world in which resources are unequally distributed in the population. Income inequality has increased in nearly all advanced economies;[1,2] in 2014 the average Gini coefficient for income inequality across OECD countries reached its highest level since the mid-1980s (0.32[3]). Perspectives on how to address income disparities are polarizing and have sown debate among researchers, policymakers, and the public.[4]

Income is concentrated within a fortunate population segment. Other types of resources are concentrated within less-fortunate segments. The modern nation-state provides services to support citizens' health, safety from crime, and economic security. The public's will to contribute to these services rests on the belief that they are equally available and can be equally used. However, health and social scientists have drawn attention to the revolving-door of hospital readmissions,[5,6] the concentration of crime,[7,8] and long-term welfare dependence.[9–11]

Here we study a segment of the population who is struggling to remain healthy, law-abiding, and economically secure, and relies disproportionately on the state. We evaluated the distributions of poor health, crime, and social-welfare use in 1.7 million New Zealanders of working age by leveraging multiple nationwide administrative data sources linked at the individual level by a common spine (the New Zealand Integrated Data Infrastructure (NZIDI[12])). We analyzed use-events in five sectors that signal health and social difficulties and burden society and government with direct and indirect costs: social-welfare benefits, public-hospital nights, prescription-drug fills, injury-insurance claims, and criminal convictions (Figure 1). We replicated analyses in nationwide registers linked to 2.3 million Danish citizens of working age.

First, we tested the hypothesis that there is concentration in the distributions of poor health, crime, and social welfare: that in each sector a small segment of the population accounts for the majority of use-events. Although studies have examined health and social inequalities in different sectors, these separate literatures have not been previously integrated in one simultaneous empirical analysis. Here we brought together administrative registers from multiple public-service sectors and employed a shared metric of inequality to compare findings across sectors at the national level. Second, we tested whether poor health, crime, and social-welfare dependency aggregate within the same individuals. It seems reasonable to assume that different segments of the population use excess health services because they are unwell, appear repeatedly in the criminal-justice system because they frequently break the

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law, and use excess social-welfare services because they cannot work. An alternative hypothesis is that people who have difficulty with health, lawful behavior, and finances share common developmental histories that impair their productive citizenship.[13–15] If so, these population segments should aggregate, and the resulting group would be a high-value prevention target. Third, we tested the hypothesis that aggregation of health and social problems is linked to individuals' preparation for a modern workforce which emphasizes labor-substituting technologies and requires increasing levels of technical skills.[16] We integrated the New Zealand nationwide administrative databases with prospective clinical data from the Dunedin Longitudinal Study, a population-representative birth cohort of 1,037 New Zealanders followed from birth to midlife with 95% retention. We focused on features of human capital in the early life-course which impact education and training potential: childhood brain health which limits primary-school readiness; adolescent mental health which affects secondary-school learning; and young-adult educational attainment. Fourth, we tested the hypothesis that aggregation of health and social problems is associated with poor life satisfaction.

New Zealand is a useful laboratory in which to study health and social inequalities. It suffers income disparities comparable to the United States and United Kingdom (after-tax Gini coefficient: NZ=0.35, US=0.39, UK=0.35[17]), has a democratically-elected government, and has cradle-to-grave public healthcare and social-welfare systems. New Zealand ranks similarly to the US and UK on the United Nations' Human Development Index (2016 report: NZ=13, US=10, UK=16[18]), and the prevalence of psychiatric illness across these countries is comparable[19] (although the suicide rate is higher in New Zealand). Importantly, New Zealand's nationwide administrative data sources were recently linked at the person level, providing an opportunity to study inequality in the distributions of multiple health and social difficulties. Denmark is an ideal country for replication. Its public-service systems are structured similarly to New Zealand's, and its national registers are also linked at the individual level. However, income disparities are less marked in Denmark (after-tax Gini coefficient=0.26[17]), enabling a test of whether health and social inequalities scale with income inequality.

Results

Marked inequality in the distributions of poor health, crime, and social welfare

In the 10-year period between July 2006 and June 2016, 27.8% of the New Zealand study population received social-welfare benefits, totaling 18,977,164 benefit-months; 37.9% were admitted to public hospitals, totaling 6,469,382 bed-nights; 94.9% filled prescription drugs, totaling 149,188,627 fills; 79.3% filed injury-insurance-claims, totaling 5,011,953 claims; and 10.7% were convicted for adult crimes, totaling 721,539 convictions (Figure 2A). Sex and age differences were in the expected direction; for instance, more men than women were convicted of crime and more young than older citizens relied on social welfare. In general, the rank-ordering on prevalence of health- and social-service involvement was consistent across men, women, and the working-age lifespan (Figure 2B).

We calculated Gini coefficients to measure inequality in the distribution of use-events in each health and social-service sector. The coefficients, which can range from 0.0 (perfect equality) to 1.0 (perfect inequality), were consistently very high, ranging from 0.96 for crime to 0.86 for social welfare to 0.54 for injury claims (Figure 2C). As a benchmark, the after-tax Gini coefficient for income inequality in South Africa–the country with the greatest degree of income inequality in the world–is 0.62.[17] Although there was modest variability across sex and age, use-events were highly concentrated in all groups (Figure 2D).

We defined a high-need group in each sector as 10% of the study population who accounted for a disproportionate share of use-events in that sector. High-need group members used 73.4% of the population's welfare benefits; occupied 85.6% of all hospital-bed nights; filled 62.1% of all prescriptions; made 36.0% of all injury claims; and were convicted of 100.0% of crimes charged to the population (Figure 3).

High-need groups' economic impact was also substantial. During the observation period, the high-need group in each sector accounted for 74.0%, 65.4%, 60.3%, and 33.5% of all New Zealand dollars spent on, respectively, social welfare, hospitalizations, prescription fills, and injury claims (Figure 3). We could not monetize crime because crime entails intangible costs that are difficult to estimate, such as victim suffering.[20] Further, any method is likely to largely underestimate costs, as many crimes (e.g., thefts, drug offenses) are not typically included in cost studies.[21] (Although we were unable to monetize crime, only 10.7% of the population had a conviction during the 10-year observation period, indicating that the 10% highest-need users accounted for virtually all dollars spent in this sector.)

Poor health, crime, and social-welfare dependency aggregated within the same people

High-need users in one sector were more likely to reappear as high-need in other sectors too (Figure 4A; Supplementary Table 3). As anticipated, there was aggregation among the health sectors: high-need users in the hospital sector had an over seven-fold increased odds of being high-need users in the pharmaceutical sector (odds ratio (OR)=7.69, 95% confidence interval (CI) [7.59, 7.78], $p<0.001$). However, more surprising, overlap was also observed across the full range of health and social-service domains. The sole exception was in the low likelihood of welfare beneficiaries making injury claims (OR=0.81 [0.80, 0.83], $p<0.001$). This is likely because the primary role of the injury claim is to replace wages lost due to injury, and social-welfare recipients do not lose their income following injury. Aggregation of poor health, crime, and social-welfare dependency was observed across men, women, and the working-age lifespan (Figure 4B; Supplementary Table 4).

Consistent with the aggregation of use-events within the same individuals, there were differences in the numbers of use-events across sectors attributable to high- and low-need individuals. People in the high-need (top 10%) social-welfare group – compared to people in the low-need (bottom 90%) social-welfare group – had on average 6.5 times more hospital nights, 5.0 times more prescription fills, 0.9 times more injury claims, and 9.3 times more criminal convictions during the observation period. People in the high-need hospital group – compared to people in the low-need group – had on average 3.0 times more benefit months, 5.0 times more prescription fills, 1.2 times more injury claims, and 2.8 times more convictions. People in the high-need pharmaceutical group had on average 3.7 times more benefit months, 10.9 times more hospital nights, 1.3 times more injury claims, and 1.7 times more convictions. People in the high-need injury-claims group had on average 0.9 times more benefit nights, 1.5 times more hospital nights, 1.6 times more prescription fills, and 1.5 times more convictions. People in the high-need convictions group had on average 3.9 times more benefit months, 2.3 times more hospital nights, 1.7 times more prescription fills, and 1.2 times more injury claims.

Also consistent with the aggregation of use-events within the same individuals, the observed distribution of high-need users across multiple sectors deviated from the expectation of a random distribution ($\chi^2_{(5)}$=291476.55, p<0.001; one-tailed test as the chi-squared distribution is asymmetric). There were more individuals than expected who did not belong to any high-need group (observed-to-expected ratio=1.12) and more individuals than expected who belonged to multiple high-need groups (observed-to-expected ratio=3.11 for three high-need groups, 13.21 for four high-need groups, and 66.77 for five high-need groups; Supplementary Results). This resulted in a small segment of the population leaving a big footprint on public-service costs: individuals who were high-need users in three or more sectors comprised only 3.7% of the study population, but accounted for 21.6% of New Zealand dollars spent on health and social services. In contrast, individuals who were not members of any high-need sectors comprised 64.2% of the population and accounted for only 19.6% of New Zealand dollars spent. Among individuals who were members of three or more high-need groups, the annual cost per person for health- and social-service provision was NZ$22,600. Among individuals who were members of no high-need groups, it was NZ $900 (Supplementary Table 5). Although our data cannot resolve causality, they suggest that intervention and policy initiatives that are successful in preventing membership in multiple high-need groups could yield an annual return of at least NZ$21,700 per person. Preventing membership in just one high-need group may also yield substantial returns (Supplementary Table 5). These are likely underestimates as they do not include costs for crime or indirect social and private costs, such as the cost of life lost due to mortality. For instance, 7.6% of individuals who were members of three or more high-need groups died during the observation period, compared with 0.7% of individuals who were members of no high-need groups. (Note, however, that we cannot infer from these data a causal association between high-need group membership and premature death.)

Inequality and aggregation were also marked in Danish nationwide records

We replicated analyses of inequality and aggregation in Danish nationwide records linked to 2.3 million citizens, using the same age population and observation years as in New Zealand. We analyzed information about three parallel sectors that were available to us: social welfare, hospital nights, and crime. During the 10-year observation period, 21.8% of the replication population received social-welfare benefits, totaling 31,643,808 benefit-months; 42.5% were admitted to public hospitals, totaling 10,250,365 bed-nights; and 7.7% were convicted for adult crimes, totaling 391,616 convictions. Gini coefficients of inequality were consistently very high and were strikingly similar to those obtained in the New Zealand registers. The coefficients ranged from 0.96 for crime to 0.88 for social welfare to 0.87 for hospital nights (Figure 5A). Also consistent with findings in the NZIDI, poor health, crime, and social-welfare dependency aggregated within the same people. High-need users in one sector were more likely to reappear as high-need in other sectors too (Figure 5B). (Because

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only 7.7% of the replication population had a conviction, the high-need group in this sector comprised the top 7.7% rather than the top 10% of users.)

Aggregation of health and social problems was linked to human-capital formation

We tested whether the aggregation of health and social problems was predicted by features of human capital important for workforce readiness. We linked 2013 NZ census data to the NZIDI spine to test associations between early school-leaving and high-need group membership. Leaving secondary school without qualifications impedes educational and vocational opportunities.[22] Early school-leaving characterized citizens who belonged to high-need groups in multiple sectors across the working-age lifespan, although the association was stronger among younger than older individuals (1980-84 age-band: incidence rate ratio (IRR)=2.25 [2.21, 2.30], p<0.001; 1950-54 age-band: IRR=1.61 [1.58, 1.64], p<0.001; Figure 6A). This cohort difference could be consistent with increasing workforce demands for recent generations to get more education and training.

We then turned to the Dunedin Study. This cohort was of the same age during the observation period as the NZIDI-derived population's 1970-1974 age-band. We linked the members of this cohort to the same administrative records in the same five health and social sectors, defined parallel high-need groups (top 10% of users in each sector), and counted the aggregation of membership across the high-need groups (Supplementary Table 6). We leveraged the prospective clinical data collected in past decades of this study to test three predictors of high-need group membership which impact education and training potential and are salient intervention targets.

First, we evaluated young-adult educational attainment. Consistent with results in the NZIDI, early school-leaving characterized Dunedin participants who belonged to high-need groups in multiple sectors 20 years later (IRR=2.92 [2.36, 3.61], p<0.001; Figure 6B). Second, we evaluated adolescent mental health using diagnoses of mental disorders made at ages 11-15 years. Mental-health difficulties interfere with adolescents' ability to engage with and benefit from secondary schooling.[23,24] Poor adolescent mental health characterized individuals who belonged to high-need groups in multiple sectors 23 years later (IRR=2.46 [2.00, 3.02], p<0.001; Figure 6C). Third, we evaluated childhood brain health (a measure combining a pediatric neurology exam and standardized cognitive and behavioral testing at age three years), which represents a child's readiness to enter school and benefit from primary education.[25,26] Poor childhood brain health characterized individuals who belonged to high-need groups in multiple sectors 35 years later (IRR=0.98 [0.97, 0.98], p<0.001; Figure 6D). Effect sizes ranged from absolute values of 0.47 to 0.68 (Cohen's *d*) and 0.24 to 0.32 (Pearson's *r*; Supplementary Table 7).

To what extent do these findings depend on poor physical health?

It is possible that the aggregation we observed was attributable to poor physical health, which might lead individuals to rely disproportionately on hospital services, pharmaceutical services, and sickness and disability benefits. We tested this hypothesis by removing sickness and disability benefits from the social-welfare sector and re-estimating the overlap among the high-need groups. Although some estimates were attenuated, aggregation was still present. High-need users in the social-welfare sector had an over three-fold increased odds of being high-need users in the hospital and crime sectors, and an over four-fold increased odds of being high-need users in the pharmaceutical sector. Welfare beneficiaries continued to have a low likelihood of making injury claims (Supplementary Table 8). Providing further evidence that the aggregation was not just attributable to illness, of individuals who were high-need users in three or more sectors, 57.8% were high-need in the social-welfare sector (excluding sickness and disability benefits), 36.2% were high-need in the injury-claims sector, and 52.1% were high-need in the crime sector (Supplementary Table 9). Finally, in the Dunedin Study we also evaluated the association between childhood physical health (described in the Supplementary Methods) and the number of high-need groups to which individuals belonged in adulthood. Poor childhood physical health tended to characterize individuals who later belonged to multiple high-need groups (IRR=1.23 [1.10, 1.36], $p<0.001$), but the effect size was approximately 50% to 60% smaller than the effect sizes for childhood brain health, adolescent mental health, and young-adult educational attainment (Supplementary Table 7).

High-need users felt their lives lacked value

High-need users were less educationally prepared for modern workforce demands; had difficulty remaining healthy, law-abiding, and economically secure; and were more reliant on public services. In addition to monetary costs borne by the state, low workforce preparedness and associated factors (for instance, poor mental health) may confer costs to an individual’s wellbeing. We therefore asked how high-need users viewed their own life circumstances, using the 5-item “Satisfaction With Life” scale. The scale was approximately symmetrically distributed (skewness=-0.59). In adulthood, individuals who belonged to high-need groups in multiple sectors reported they were dissatisfied with life (β=-0.28 [-0.34, -0.21], $p<0.001$). Individuals who belonged to three or more high-need groups reported a level of life satisfaction one standard deviation lower than individuals who belonged to no high-need groups (Figure 6E).

Discussion

Scientists and policymakers are looking to big data to provide unbiased estimates of population-level phenomena.[27,28] Our analysis responds to this demand, and yields two insights.

First, we brought together multiple nationwide registers which allowed us to uncover a population segment that featured as both high-need and high-cost across different health and social sectors. The segment was present across men, women, and the working-age lifespan; and was evident in two nations with different income distributions. This illustrates the high discovery value offered by linking nationwide administrative databases at the individual level. Tomorrow’s jobs will require more training and specialized skills. The population segment identified here is already having difficulty making this transition. Their ability to contribute to the evolving labor force is limited by multiple challenges: high-need users were less ready to be trained for the workforce; struggled to stay healthy, stay self-supporting, and stay out of trouble; and were less satisfied with their lives.

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Second, by integrating nationwide administrative data sources with prospective clinical information, we identified a small set of human-capital factors that predicted membership in this population segment. Individuals who belonged to multiple high-need groups had the poorest childhood brain health, exhibited the highest rates of adolescent psychiatric disorders, and were the most likely to leave secondary school prematurely. These malleable risk factors interfere with workforce readiness and are already the focus of prevention programs.[29–32] If established interventions are effective at improving the high-need population segment's trainability for the modern workplace, they might yield substantial returns on investment.

This research has limitations. First, results for the oldest age-bands may be biased by selective mortality of high-need individuals, which would reduce concentration. Thus, our findings reflect conservative concentration estimates for older age groups. Conversely, many young university-educated New Zealanders spend a year abroad; selective absence of these lower-need individuals could bias the youngest age-bands, but analyses were adjusted for time abroad. Second, matching to NZIDI databases is conducted using probabilistic algorithms, which are subject to error. However, all individuals in our study population were linked to the NZIDI spine, and false-positive linkage errors were rare (≤ 0.6% for all age-bands). Moreover, findings in the NZIDI were replicated in Danish administrative records, which linked registers with a personal identification number, and in the Dunedin Study, which was able to conduct individual-level matching by hand using multiple forms of archived identifying information to resolve any uncertain matches. Third, our birth-cohort approach was a practical means by which to define our study and replication populations, but it necessarily excludes in-migrants. Fourth, although our population-segmentation approach was a straightforward and practical way to capture concentration and identify a group of citizens in need of early intervention, such supports are also relevant for vulnerable individuals who fall outside the 10% cutoff. Fifth, we measured direct government costs associated with health and social services, which may have resulted in underestimates for some sectors. For instance, unemployment benefits incur not only the costs of benefit payments, but also lost GDP resulting from individuals' inactivity in the labor market. We also did not include the other social and private costs that may result from high-need group membership, including reduced personal income and government tax revenue, skill erosion, reduced fertility, fewer educational opportunities for offspring, and increased taxation on businesses to cover the costs of unemployment benefits. Finally, our observational research can only support poor childhood brain health, poor adolescent mental health, and early school-leaving as indicators of risk for high-need group membership; the risk factors we studied are not necessarily causal.

These findings have a number of implications. First, they suggest that a portion of the population is likely to be left behind without sufficient supports to meet the demands of the changing employment landscape. This portion of the population is becoming a central focus of international policy debate. Several countries have implemented trials of a universal basic income.[33] Universal basic income schemes use government transfers to support all citizens, including well-educated citizens who may be affected by technological unemployment. However, these schemes may be particularly relevant for members of the high-need population segment identified here, who are likely to be disproportionately affected by

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workforce changes. In addition, there is increased attention to developing workforce strategies to promote adaptation to the “Fourth Industrial Revolution” among young people at risk for occupying the high-need population segment when they reach adulthood.[16] The gap between individuals’ skills and labor-force expectations is likely to widen without national investments to reduce inequality in education and training capacity.[34,35]

Second, we identified three targets across three developmental periods toward which interventionists and policymakers might consider directing such efforts: brain health and school readiness in early childhood, mental health in adolescence, and educational attainment in young adulthood. There may be other intervention targets that we were unable to study, and it is possible that those we studied are proxies for other risk factors. However, we evaluated these particular three factors because they are modifiable and already embedded within prevention programs, which implies that there is a high probability for translation to implementation. Education and mental health are the targets of vigorous research testing causal effects on later health and employment (e.g.,[36,37]), but causation remains controversial and population-level tests are needed. Further, there is some debate about the optimal timing for delivering interventions, and whether programs implemented in the youngest years are most effective.[14,38,39] The effect sizes reported here suggest that if associations are causal, investing in individuals’ education and training potential across multiple stages of the early life-course could yield substantial returns in the form of reduced health and social inequalities. Such returns are likely to be reflected not only in economic markers of productivity and reduced public-service use, but also in citizens’ subjective experience of a satisfying life.[37,40]

Third, inequality and aggregation of health and social problems are evident across the life-course. It is perhaps unsurprising that accidental injuries and crime go together among young people, as do social-welfare dependency and ill health among midlife adults. However, overlap between poor health and crime among individuals nearing retirement age is less expected. Coordinated service delivery has traditionally been targeted toward young people and families.[41,42] The present data suggest that integrated-care models may also benefit midlife-to-older adults. Such systems can help ease the transition into, but also out of, the working years.

Lastly, we acknowledge the potential for these findings to be misused. Population segments are often stereotyped, and estimating a group’s economic burden immediately lends itself to stigmatizing reactions. However, avoiding identifying vulnerable groups due to potential for stigma may unintentionally leave the most vulnerable citizens without supports. In addition, we considered it important to monetize outcomes to clarify the potential return on early-years intervention. Individuals who belonged to multiple high-need groups are few in number, but account for a disproportionate share of economic costs. However, imparting blame will not ameliorate social inequality or economic burden. Instead, increasing opportunity for productive citizenship could benefit all members of a society, including those to come. New Zealand Prime Minister Jacinda Ardern echoed this perspective in her 2018 speech at the United Nations: “The transitions our economies have made have often been jarring, and the consequences harsh…. Digital transformation will determine whether the jobs [young people] are training for will even exist in two decades…. We must show the next generation that we are listening, and that we have heard them.”[43]

Methods

A more detailed description of the study design, measurement, and statistical analysis is included in the Supplementary Methods.

Study population: New Zealand Integrated Data Infrastructure

Participants in our study population were drawn from the Statistics New Zealand Integrated Data Infrastructure (NZIDI), a collection of de-identified, whole-of-population administrative data sources linked at the individual level by a common spine.[12]

Our study population included the 1,711,590 individuals who were born in New Zealand between 1950-1984 and resided in the country for any period of time between the July 2006-June 2016 fiscal years (age 22-66 years; Supplementary Table 10; Figure 1). We selected this age range to maximize representation of post-education, pre-retirement lives. Reliable electronic data capture was present for all administrative sectors of interest starting in July 2006. We divided the population into seven four-year age-bands (Supplementary Table 10).

We excluded individuals who had evidence of a death in New Zealand prior to the observation period, an overseas spell spanning the entire observation period, or no evidence of residence in New Zealand during the observation period. Information about mortality, travel, and residency were recorded by the New Zealand Department of Internal Affairs; by the New Zealand Ministry of Business, Innovation and Employment; and in the NZIDI Resident Population Table, respectively.

Data analysis was approved by Statistics New Zealand-Tatauranga Aotearoa. The Health and Disability Ethics Committee classified the study as “out of scope.”

Replication population: Danish nationwide registers

We replicated analyses in Danish nationwide administrative registers. The replication population covered the same birth years and 10-year observation period as the NZIDI study population, and focused on the three social, health, and justice sectors that were available to us. The replication population included 2,363,240 individuals. Data analysis was approved through a longstanding agreement between the Rockwool Foundation Research Unit and Statistics Denmark.

Dunedin Study sample

We also studied a third sample: the Dunedin Multidisciplinary Health and Development Study, which tracks the development of 1,037 individuals born in 1972-1973 in Dunedin, New Zealand.[44] Included in the present report were complete data from 940 Study members (93.3% of the 1,007 participants alive at the phase-38 assessment, when administrative-record linkage was performed[13]). The Otago University Ethics Committee, Duke University, and King’s College London provided ethical approval for the Dunedin Study and Study members gave informed consent before participating.

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Poor health, crime, and social-welfare dependency

We collected information from the NZIDI about five health and social sectors. Information about social-welfare benefits was recorded by the New Zealand Ministry of Social Development; information about bed-nights in public hospitals was recorded by the New Zealand Ministry of Health; information about prescription drugs filled by pharmacists was recorded by the New Zealand Pharmaceutical Management Agency; information about insurance claims for accidents and injuries was recorded by the Accident Compensation Corporation, the national provider of comprehensive, no-fault personal injury coverage for New Zealanders; and information about criminal convictions was recorded by the New Zealand Ministry of Justice.

In the Danish registers, information was available for social-welfare benefits, bed-nights in public hospitals, and criminal convictions.

Human-capital factors

Information about young-adult educational attainment was available in the NZIDI (for 78.9% of the study population who provided education data in the 2013 census) and the Dunedin cohort. 19.1% of the NZIDI study population left secondary school early without qualifications. 14.9% of the Dunedin Study sample left secondary school early without qualifications, which matched the rate of 14.7% for the NZIDI 1970-74-born age-band (Supplementary Table 11).

Psychiatric diagnoses at 11, 13, and 15 years of age were assessed in the Dunedin cohort using the Diagnostic Interview Schedule for Children,[45] using the then-current DSM-III criteria.[46] Study members were defined as having a mental-health diagnosis during adolescence if they met diagnostic criteria for depression, anxiety, conduct disorder, or attention-deficit/hyperactivity disorder. 35.1% of the Dunedin Study sample met criteria for a psychiatric disorder,[47] which matches the prevalence in United States epidemiological samples.[48]

At age 3 years, each child in the Dunedin cohort participated in a 45-minute examination that included assessments of neurological soft signs, intelligence, receptive language, and motor skills, and afterwards the examiners (having no prior knowledge of the child) rated each child’s behavior (Supplementary Methods). Using this information, we created a summary factor score via confirmatory factor analysis which we termed childhood brain health, a global index of the child’s early neurocognitive status.[13]

Childhood physical health

We measured Dunedin participants’ childhood physical health using a composite that included repeated measures of adiposity, blood pressure, lung function, motor function, and diseases and injuries taken when study members were age 3-11 years.[49] The composite was standardized to M=0, SD=1.

Life satisfaction

At age 38, Dunedin cohort participants completed the 5-item Satisfaction With Life Scale.[50] Participants were asked to rate how strongly they agreed with each of the following statements, on a 5-point scale (1="strongly disagree" and 5="strongly agree"): "In most ways my life is close to ideal"; "The conditions of my life are excellent"; "I am satisfied with my life"; "So far I have gotten the important things I want in life"; "If I could live my life over, I would change almost nothing." The items were summed and the resulting scale was standardized to M=0, SD=1.

Statistical analysis

Individuals who died or traveled outside of New Zealand or Denmark during the observation period had reduced time during which they were eligible to appear in government records. Failing to account for these differences in exposure time could lead to biased estimates because some individuals whose activity went unobserved would be improperly coded as "non-users" of public services, but they would have used these services if they had been alive or in the country. For example, 0.7%, 3.6%, 6.1%, and 7.6% of individuals who were members of 0, 1, 2, and 3 or more high-need groups, respectively, died during the observation period. In order to account for differences in exposure time, we used information about mortality and travel to weight the data based on time spent alive and in the country. For instance, an individual who was alive and in the country during the entire 10-year observation period was assigned a weight of 1.0, while someone who was alive and in the country during only the first five years was assigned a weight of 0.5. In the NZIDI, where we divided the study population into age-bands, the same weighting procedures were applied across all age-bands (Supplementary Table 10).

We examined the cumulative distributions of events in each of the five health and social sectors in the NZIDI study population, and by age-band and sex. Using these distributions, we assessed the degree of inequality in each sector by calculating the Gini coefficient, an economic measure of statistical dispersion traditionally used to index income inequality.[51,52]

In subsequent analyses, we defined a high-need group in each sector as 10% of the population who accounted for the most disproportionate share of use-events in that sector. This 10% cut-point was based on the sector with the lowest prevalence of use (criminal convictions) and was applied in all five sectors to allow comparisons across sectors. We tested whether high-need users in one sector were likely to be high-need users in multiple sectors using two methods. First, we added up (0-5) the number of high-need groups to which each individual belonged, and tested whether the distribution of high-need users across multiple sectors deviated from the expectation of a random distribution. Second, we used logistic regression to predict high-need group membership in one sector from high-need group membership in another sector. Analyses were conducted within the study population and by age-band and sex.

In the Danish replication population, we calculated Gini coefficients, defined parallel high-need groups, and calculated odds ratios for the overlap among the social-welfare, hospital, and criminal-offending sectors. (Because only 7.7% of the replication population had a

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criminal conviction during the observation period, the high-need group in this sector comprised the top 7.7% rather than the top 10% of users.)

In the NZIDI and Dunedin datasets, we used negative binomial regression models with incidence rate ratios to test whether early human-capital factors predicted the number of high-need groups to which an individual belonged. We used ordinary least squares linear regression to test whether high-need group membership (entered as an ordinal predictor) was associated with life satisfaction. In the NZIDI dataset (weighted for time spent outside New Zealand or deceased), models using the study population controlled for sex and age-band; models within age-bands controlled for sex. In the Dunedin cohort, models controlled for sex and time spent outside New Zealand.

Per the confidentiality rules of Statistics New Zealand, frequencies/counts were randomly rounded to a base of three and dollar values were rounded to the nearest 100 for the NZIDI data.

The project and analysis plan were preregistered (2018; https://cdm20045.contentdm.oclc.org/digital/collection/p20045coll17; https://sites.google.com/site/dunedineriskconceptpapers/home/dunedin-approved).

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

Supported by grants from the National Institute on Aging (AG032282, AG049789, P30AG034424), National Institute of Child Health and Human Development (NICHD; HD077482), U.K. Medical Research Council (P005918, G1002190), the Jacobs Foundation, and the Avielle Foundation. The Dunedin Multidisciplinary Health and Development Research Unit is supported by the New Zealand Health Research Council and the New Zealand Ministry of Business, Innovation and Employment (MBIE). Dr. Richmond-Rakerd was supported by a postdoctoral fellowship from the NICHD (T32-HD007376) through the Frank Porter Graham Child Development Institute at the University of North Carolina at Chapel Hill. Dr. Andersen was supported by the Rockwool Foundation. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. We thank Angela O'Rand. We thank the Statistics New Zealand Methods Team for their assistance.

The results in this paper are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics New Zealand. The opinions, findings, recommendations, and conclusions expressed in this paper are those of the authors, not Statistics NZ. Access to the anonymized data used in this study was provided by Statistics NZ under the security and confidentiality provisions of the Statistics Act 1975. Only people authorized by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organization, and the results in this paper have been confidentialized to protect these groups from identification and to keep their data safe. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.

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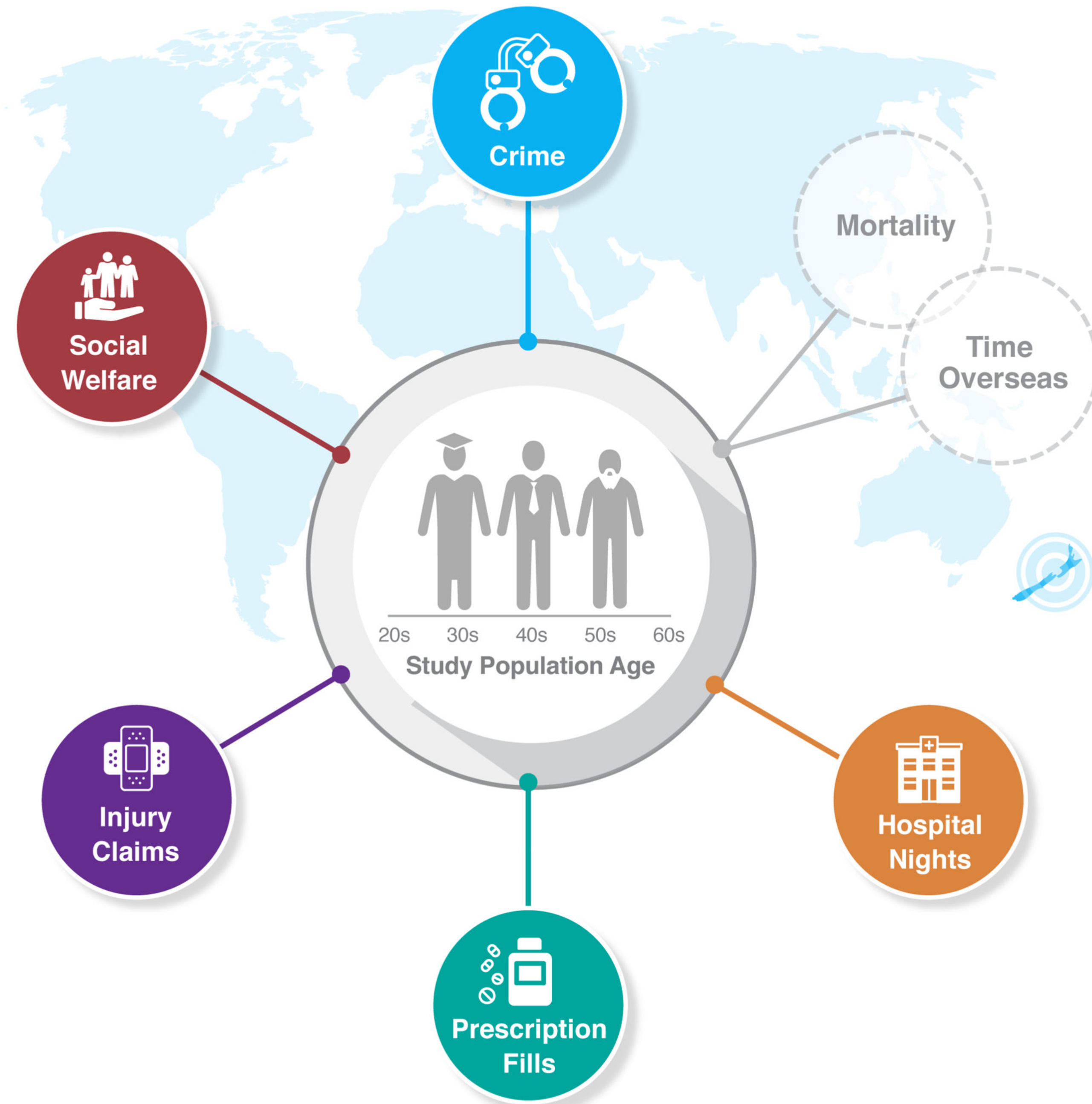

Figure 1. Nationwide data capture of poor health, crime, and social-welfare dependency in 1.7 million New Zealanders.

We obtained information about our five sectors of interest – social-welfare benefits, public-hospital nights, prescription-drug fills, injury-insurance claims, and criminal convictions – from records maintained by the New Zealand Ministry of Social Development, Ministry of Health, Pharmaceutical Management Agency, Accident Compensation Corporation, and Ministry of Justice, respectively. To account for the amount of time individuals were eligible to appear in New Zealand government records, we obtained information about mortality and time overseas from records maintained by the New Zealand Department of Internal Affairs and Ministry of Business, Innovation and Employment, respectively.

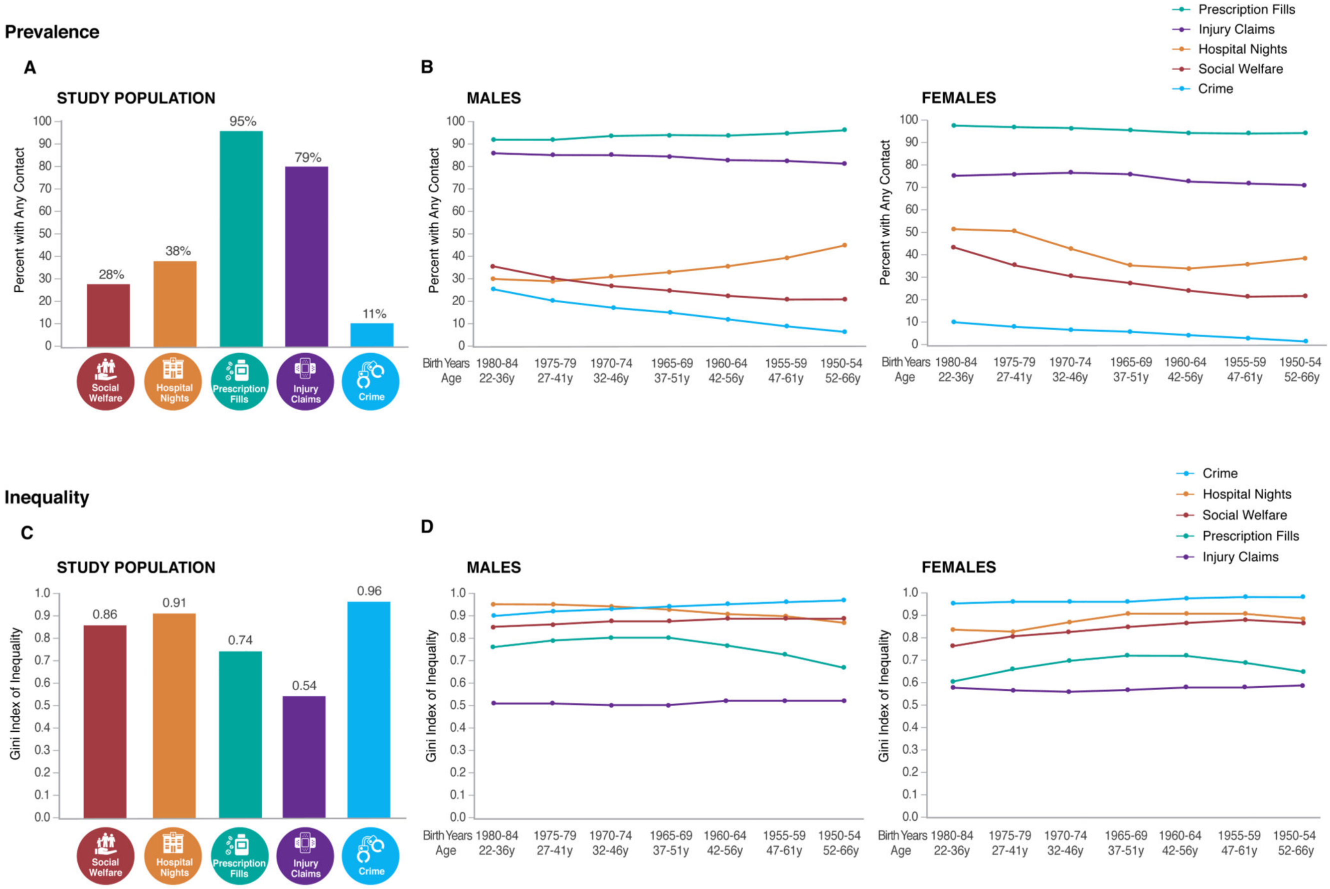

Figure 2. Inequality in the distributions of poor health, crime, and social welfare.

The figure shows that contact with health and social sectors is common, but use-events are highly concentrated. Prevalence estimates indicate the percentages of the NZIDI study population (Panel A) and each age-and-sex grouping (Panel B) that had any contact with the five health and social sectors during the 10-year observation period (July 2006-June 2016). The Gini coefficients indicate the degree of inequality in the distribution of use-events in each sector, for the study population (Panel C) and each age-and-sex grouping (Panel D). Gini coefficients can range from 0.0 (perfect equality) to 1.0 (perfect inequality). Study population N=1,711,590.[a]

[a]Randomly rounded to a base of three, per the confidentiality rules of Statistics New Zealand.

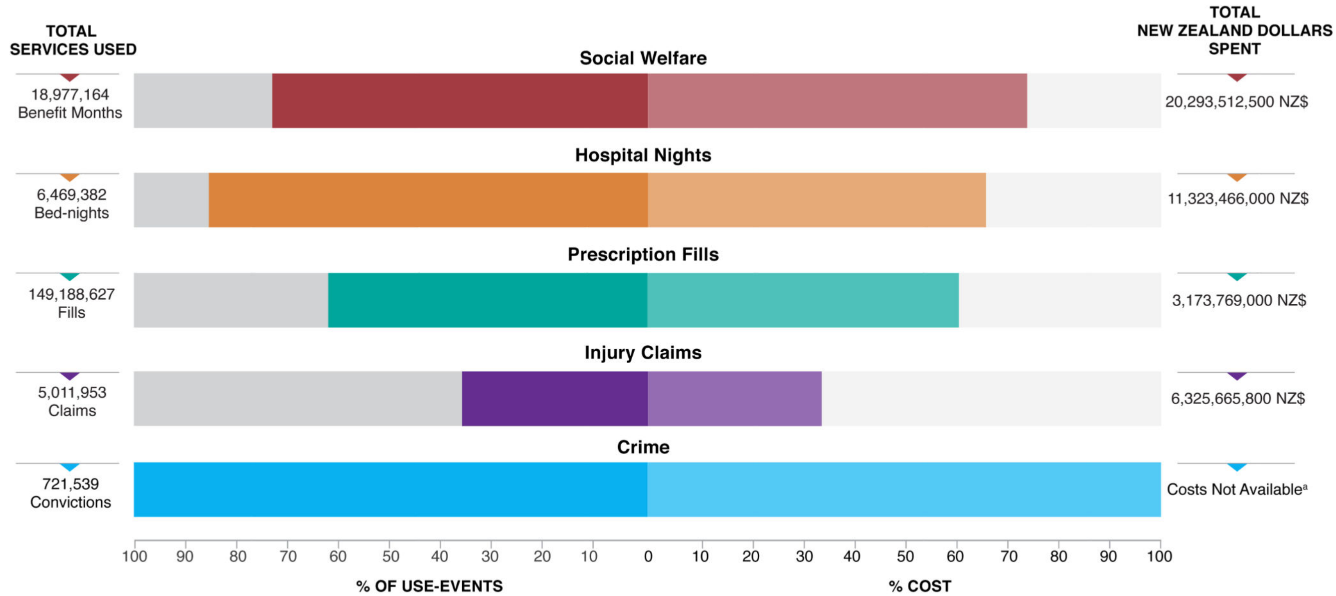

Figure 3. Impact of high-need/high-cost users.

The figure shows that in each of the five health and social sectors, 10% of the NZIDI study population accounted for a disproportionate share of use-events (left panel) and costs (right panel). Totals were accumulated across the 10-year observation period (July 2006-June 2016). Per the confidentiality rules of Statistics New Zealand, counts were randomly rounded to a base of three and dollar values were rounded to the nearest 100.

[a]Although objective costs were not available for criminal convictions, only 10.7% of the study population had a conviction during the observation period, indicating that high-need users accounted for virtually all dollars spent in this sector.

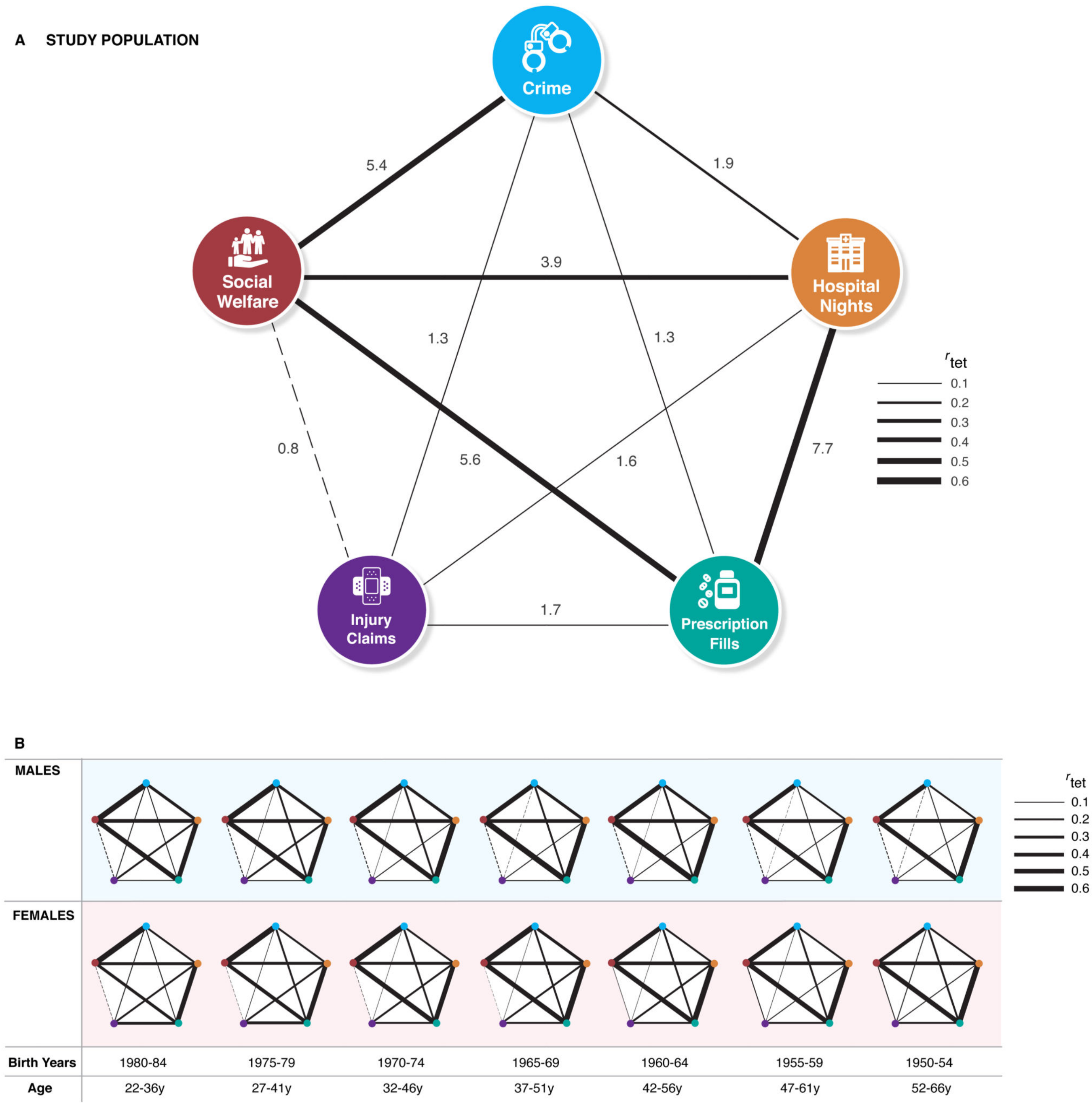

Figure 4. Aggregation of poor health, crime, and social-welfare dependency.

The figure shows that high-need users in one sector were more likely to reappear as high-need in other sectors too (with the exception of the relation between social welfare and injury claims). Estimates are odds ratios. The corresponding tetrachoric correlations (r_{tet}) were used to scale the bars. Dashed lines indicate a negative correlation. Odds ratios, 95% confidence limits, and p-values for the NZIDI study population and each age-and-sex grouping are reported in Supplementary Tables 3 and 4.

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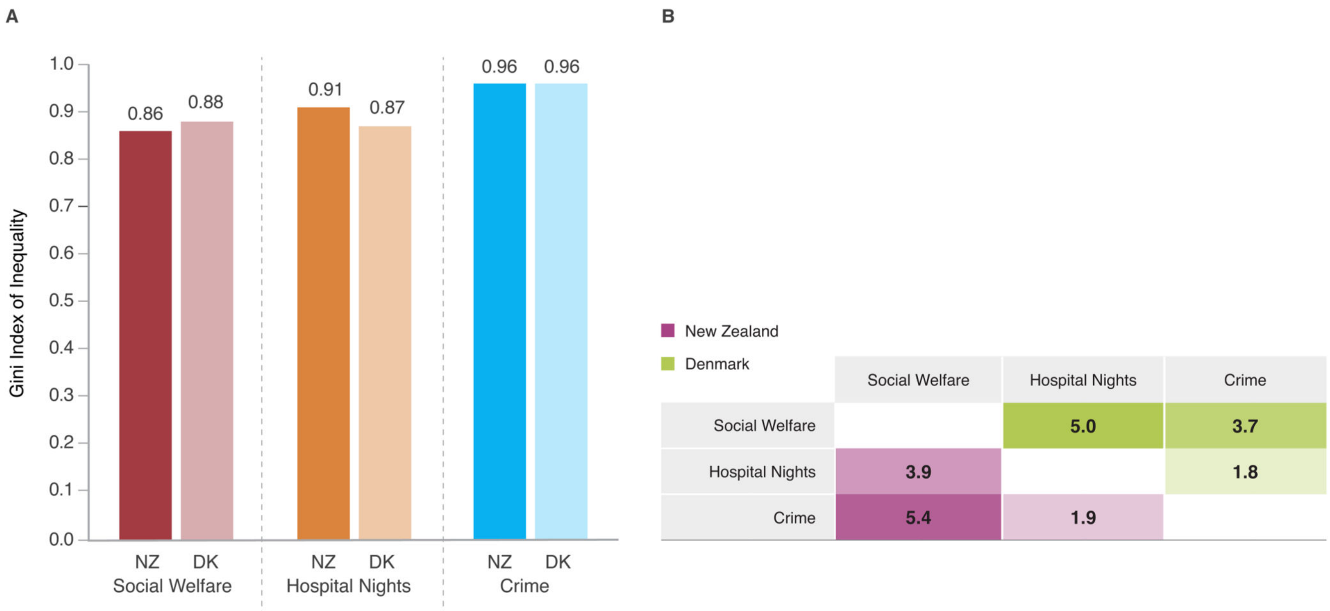

Figure 5. Replication in Danish nationwide registers linked to 2.3 million citizens.

Concentration and aggregation were also evident in Danish nationwide registers. Gini coefficients of inequality in the Danish registers were strikingly similar to those in the New Zealand registers (Panel A). Also consistent with findings in the NZIDI, high-need users in one sector were more likely to reappear as high-need in other sectors too (Panel B). Estimates in Panel B are odds ratios. The 95% confidence limits are as follows: social welfare with hospital nights (NZ=3.94 [3.89, 4.00], DK=5.00 [4.94, 5.05]); social welfare with crime (NZ=5.35 [5.28, 5.42], DK=3.74 [3.69, 3.78]); hospital nights with crime (NZ=1.93 [1.90, 1.96], DK=1.75 [1.73, 1.78]). P-values for all associations are <0.001. NZ=New Zealand, DK=Denmark.

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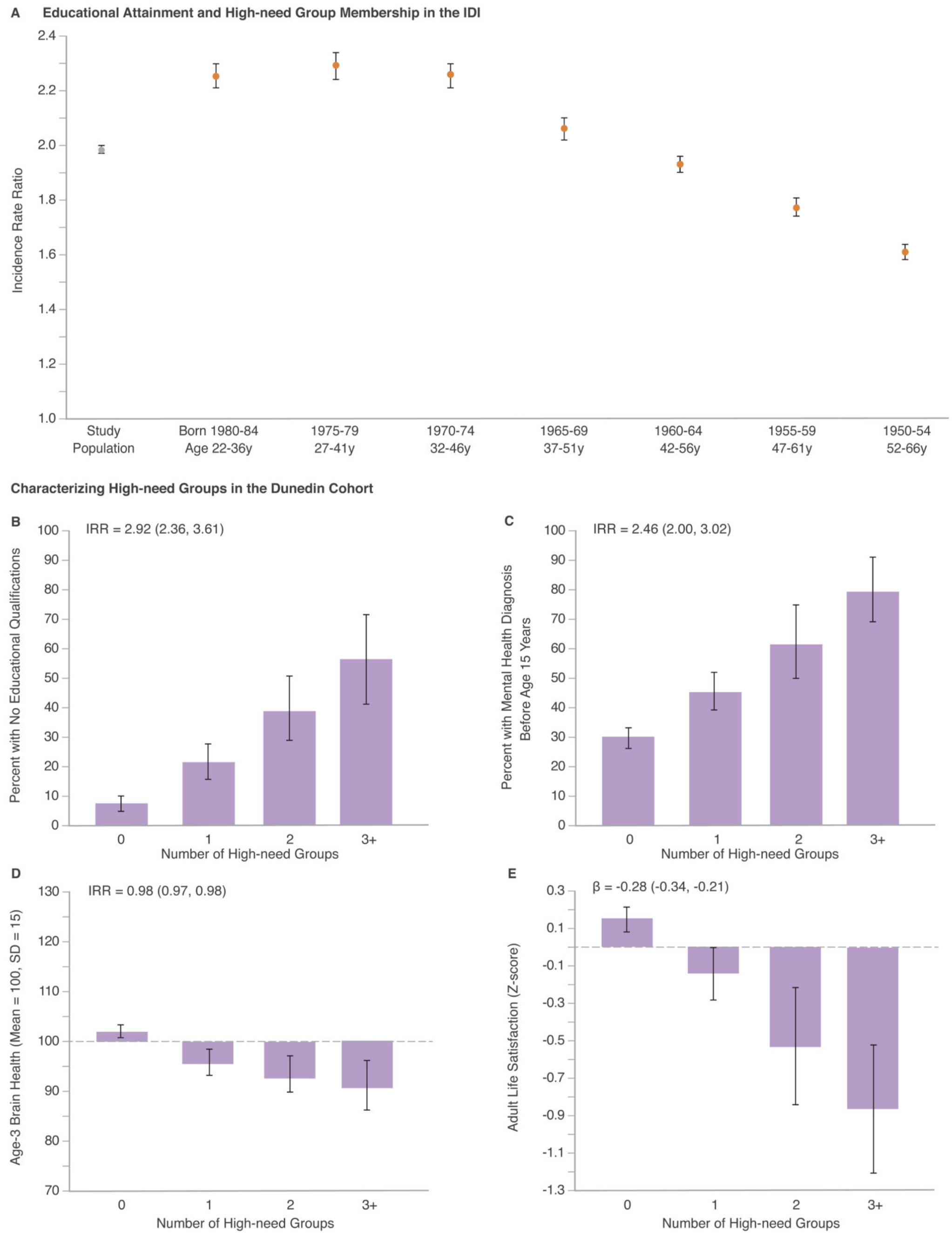

Figure 6. Characterizing high-need users.

Human-capital factors predicted the number of high-need groups to which individuals belonged. Early school-leaving (Panels A and B), early-onset psychiatric disorder (Panel C), and low childhood brain health (Panel D) characterized individuals who belonged to multiple high-need groups. The relation between educational attainment and high-need group membership was comparable in the NZIDI 1970-74-born age-band (Panel A: IRR=2.29, 95% CI [2.25, 2.34]) and the Dunedin 1972-73 cohort (Panel B: IRR=2.92 [2.36, 3.61]). In midlife, members of multiple high-need groups reported the poorest life satisfaction (Panel E). P-values for all associations are <0.001. Effect sizes (Pearson's *r* and Cohen's *d*) for the associations between human-capital factors and high-need group membership are reported in Supplementary Table 7. Error bars and values in parentheses are 95% confidence intervals. Education data were available for 78.9% of the NZIDI study population. Dunedin cohort N=940. IRR=incidence rate ratio.