Pathways into Homelessness*

Pierre-Loup Beauregard†
Université de Montréal

Victor Couture§
University of Toronto

David A. Green‡
University of British Columbia

Jeffrey Hicks¶
University of Toronto

William Warburton||
Enterprise Economic Consulting

July 2026

Abstract

We investigate the determinants of homelessness by documenting complete life trajectories leading to a first spell. We use a panel of linked administrative records from healthcare, criminal justice, education, and social assistance for the full population of British Columbia. Future homeless individuals face severe disadvantage beginning in childhood: over half had contact with child welfare services, and fewer than a quarter graduated from high school. In the months before onset, emergency room visits, mental health and substance use treatment, and alleged crime rise sharply. These rich histories identify a high-risk group whose rate of first entry into homelessness, out of sample, is 25 percent over the following year, roughly 80 times the population rate. A handful of risk factors, capturing substance use, criminal justice involvement, and poverty, identify this group almost as well as the full model. These findings offer the most comprehensive picture to date of the risk factors for homelessness, and show that entry is predictable from data collected at points of contact with government services.

Key words: homelessness, poverty, housing, opioids, crime, machine learning
JEL classification: I32, R31

*The following material was developed as part of a project titled "Pathways Into Homelessness" (University of British Columbia (UBC), University of Toronto (UoT)), Province of British Columbia. The results in this paper have been created from information made available through the Data Innovation Program. The following data sets were used: BC Employment and Assistance, Discharge Abstract Database Core, Census Geodata, Client Roster, Contiguous Client Roster, Health Registry and Demographics, Chronic Disease Registry, Medical Services Plan (MSP), National Ambulatory Care Reporting System, PharmaNet, BC Vital Events and Statistics, Shelter and Homeless Outreach Private Market Rent Supplement, Private Market Rent Supplements for Eligible Seniors and Working Families, Supportive Housing, Child Welfare Program, Corrections - Adult Community and Custody, K to 12 Student Demographics and Achievement. Further information on the datasets used for this project is at: catalogue.data.gov.bc.ca/datasets. All inferences, opinions, and conclusions drawn in these materials are those of the authors. They do not reflect the opinions or policies of the provider(s) of the data upon which they are based. Ingrid Monsivais Ibarra provided tremendous research assistance. Alex Jutca provided excellent comments. Hicks acknowledges funding from Data Sciences Institute at the University of Toronto (DSI-CQSSY5R1P14) and the Social Sciences and Humanities Research Council.

†UdeM, Department of Economics (email: `pierre-loup.beauregard@umontreal.ca`)

§UofT, Rotman School of Management (email: `victor.couture@utoronto.ca`)

‡UBC, Vancouver School of Economics (email: `David.Green@ubc.ca`)

¶UofT Scarborough (email: `jeffrey.hicks@utoronto.ca`)

|| Enterprise Economic Consulting (email: `billwarburton8@gmail.com`)

1. Introduction

Homelessness is the most extreme form of poverty in rich countries. Its severe consequences and many of its correlates are well-documented, but the risk factors that precede a first spell remain poorly understood. In this paper, we investigate the determinants of homelessness by documenting complete life trajectories. We use a new panel of linked administrative records that is more comprehensive than any dataset previously used to study homelessness. These data cover the full population of British Columbia, a Canadian province, and link records from several provincial ministries covering child welfare, education, healthcare, social assistance, and criminal justice from 1996 to 2024. We follow individuals starting from childhood, with high-frequency data that capture events in the months immediately preceding homelessness. These complete life histories allow us to distinguish long-term childhood disadvantages from the acute shocks in adulthood that can precede homelessness.

We find that over half of future homeless individuals had contact with child welfare services during childhood and fewer than a quarter graduated from high school. In the months before onset, emergency room visits, mental health and substance use treatment, and alleged crime rise sharply. Using a hazard model, we rank individuals each month by predicted risk and identify a group that is, out-of-sample, roughly 80 times more likely than the general population to become homeless in the following year. Just five risk factors, drawn from substance use, criminal justice involvement, and poverty, identify this group nearly as well as our full model.

Our investigation is important for three reasons. First, effective prediction is a prerequisite for cost-effective prevention. Homeless individuals generate high public costs: in Los Angeles, public spending is roughly six times higher for unemployed workers who become homeless than for those who do not (Toros, Flaming, and Burns, 2019); in our setting, homeless individuals incur 9.3 times the government health expenditures of the general population. Evidence suggests that relatively modest interventions can prevent entry for some individuals (Phillips and Sullivan, 2024, Evans, Sullivan, and Wallskog, 2016). But because homelessness is rare, broad-based programs risk allocating resources to many individuals who would have remained housed without assistance. In British Columbia, homelessness has risen despite broad cash support, with annual amounts exceeding the one-time and short-term assistance that US prevention programs have tested.[1] Identifying those at acute risk could help target intervention efficiently.[2]

Second, homelessness is a key marker of vulnerability that our data show is associated with chronic mental illness, head injury, substance use disorder, and increased mortality. The risk factors predicting entry thus serve as an index of extreme vulnerability more

[1] Monthly income assistance in BC is approximately equal to the median rent for a one-bedroom apartment in the province.

[2] Many jurisdictions also have emergency services to help people as soon as they are reported as homeless.

broadly, one that can help governments target support to those in greatest need, including in childhood well before housing instability begins.

Third, understanding individual-level risk factors may shed light on the rapid aggregate rise in homelessness in British Columbia over the last two decades, a trend shared with some other jurisdictions in North America (Meyer, Wyse, Grunwaldt, Medalia, and Wu, 2021). We find that entry into homelessness is strongly associated with prior criminal justice involvement, poverty, and substance use disorders. Poverty and crime rates have declined since the mid-2010s (Statistics Canada, 2026), however, when the rise in homelessness accelerated, making them less likely to drive the trend. Among the individual factors we consider, substance use appears as a plausible candidate: it is highly predictive, common, and rising with the opioid crisis and the spread of fentanyl (Appendix Figure E.1). Housing costs also rose alongside homelessness at the provincial level. Across cities, however, the hazard model shows no positive association between time trends in rents and homelessness entry.[3] Housing costs may still have played a role, of course, through the province-wide increase or other channels that our city-level comparison cannot isolate.

Our analysis combines three main measures of homelessness. First, we identify individuals designated as having "no fixed address" for at least three consecutive months by British Columbia's income assistance and disability assistance (IA/DA) programs. This captures a wide variety of housing instability, from couch surfers to the unsheltered. Second, we include individuals recorded in homeless shelters, using data available from 2018 onward. Third, we identify individuals flagged with homelessness diagnosis codes during hospital visits. Because BC's income assistance is available to all household types—including single men, who are the majority of the homeless—and healthcare is almost entirely public, these records capture a broader population than is typically possible with US data. Combining the three sources reveals a rapid rise in homelessness starting in the mid-2010s. This trend is in part attributable to longer spells rather than to rising inflows alone.

We begin our characterization of the life trajectories of the homeless population by comparing individuals who are currently homeless with the general population and with IA/DA recipients who are housed. Linking to childhood records shows that the homeless population is characterized by long-term disadvantage along nearly every measurable dimension. 51% had interactions with the child welfare agency as children (under formal supervision or in foster care), compared with only 4% of the general population and 24% of housed IA/DA recipients. Educational outcomes are similarly stratified: only 22% of the homeless population graduated from high school, compared to 81% of the general population and 34% of housed IA/DA recipients. Nearly half of homeless individuals had an inclusive education designation (behavioural, intellectual, or physical) during high school, compared

[3]This lack of sub-provincial positive association between time trends in rents and homelessness entry is robust across specifications and sample periods.

to fewer than one in ten in the housed population. In adulthood, we document profound disparities in health, substance use, and criminal charges. For example, 17% of the homeless population were diagnosed with schizophrenia, compared to roughly 1% of the general population, and 68% were diagnosed with a substance use disorder, compared to 6% in the general population. These comparisons, however, cannot distinguish whether adverse events precede homelessness or result from it.

To distinguish risk factors from consequences, we estimate event studies that track the precise timing of adverse events relative to the start of a first homelessness spell. We consider ER visits, receiving income or disability assistance, allegedly committing a crime, and treatment for head injury, mental health, and substance use, among other outcomes. Economic and social indicators deteriorate gradually in the years prior to a first homelessness spell. Criminal justice events and health shocks, by contrast, accumulate rapidly in the months immediately preceding entry and remain elevated thereafter. For each of these events, we report both the likelihood and Bayes factor. Criminal justice interactions, for instance, are rare even in the homeless population (low likelihood) but highly predictive of homelessness when they occur (high Bayes factor). Treatment for substance use disorders is both common and predictive.

These patterns imply that both long-term disparities and adverse events are associated with entry into homelessness. These individual risk factors, however, are highly correlated. To rank the factors most strongly associated with entry, we estimate a proportional hazard model of first entry into homelessness. This model yields interpretable estimates of each risk factor's relation to homelessness entry, all else equal. The results confirm that homelessness is the culmination of long trajectories. Among childhood events, failing to graduate from high school carries the highest risk. Ongoing adult conditions raise risk even more. A long-standing substance use disorder more than quadruples the monthly risk of entry, conditional on all other risk factors. Being a long-standing income assistance recipient more than triples it, and being single and childless more than doubles it. Recent adverse events carry comparable risk. In the three months before entry, an alleged crime or a new substance use diagnosis each more than triple it. When we estimate the model separately for entry into short spells (under seven months) and long spells (seven months or more), we find similar hazard ratios and rankings of risk factors across the two.[4] Although these estimates are not causal, the accumulation of adverse events in the months before onset makes the timing of entry predictable, an important policy objective in its own right.

The hazard model serves as our baseline predictor of who will enter homelessness in the next 12 months. We validate it out of sample by predicting first entry in 2023 and 2024. Among the 0.025 percent of the population the model ranks as most at risk in a given month,

[4]People who go on to experience long spells are more disadvantaged on every dimension we measure, from adverse childhood outcomes to crime, substance use, and emergency visits in adulthood, both before and after the onset of homelessness.

24.6 percent become homeless over the following year, a hazard 79 times that of the general population. A separate question is how much of all entry the model captures. The top three percent of predicted risk account for half of all first entries. A model using only childhood risk factors identifies a group entering homelessness at twenty times the population rate over the following year. These factors are fixed in childhood, yet they capture homelessness risk in any given adult year.

A series of extensions verify that our hazard model still predicts well in more common settings lacking records as rich as ours. Removing every childhood variable barely changes predictive performance, because these variables are closely correlated with the adverse events people experience later in life. A model using only the five risk factors a LASSO selects as jointly most predictive does almost as well at identifying the most at-risk, but underpredicts modestly in the medium-risk group. All five factors fall under substance use, criminal justice involvement, or poverty. They include a long-standing substance use disorder and a recent alleged offence, the two highest ranked risk factors in our baseline model.

The risk factors we identify could help policymakers target prevention. They are observed at points of contact with hospitals, the courts, and social assistance offices, where a policymaker could act on them. We also estimate the model on social assistance recipients alone, a population already in monthly contact with the government, and find that the same factors identify those at high risk of entry.

Our main contribution is to identify the risk factors of homelessness with greater detail, frequency, and comprehensiveness than any prior study. The Australian Journeys Home project (Cobb-Clark, Herault, Scutella, and Tseng, 2016, McVicar, Moschion, and van Ours, 2015, Moschion and van Ours, 2019, Scutella, Johnson, Moschion, Tseng, and Wooden, 2012, Wooden, Bevitt, Chigavazira, Greer, Johnson, Killackey, Moschion, Scutella, Tseng, and Watson, 2012, among others) produced pioneering work on trajectories into homelessness. But the Journeys Home studies rely on self-reported surveys from approximately 1,700 individuals drawn from welfare agency files. Our administrative data cover the full population of British Columbia and avoid the recall and reporting concerns inherent in self-reported survey data.

Particularly prominent recent work is by Meyer, Wyse, and co-authors, who link US Census and American Community Survey data to tax records, food benefits, housing assistance, and Medicare/Medicaid coverage (Meyer et al., 2021, Meyer, Wyse, and Logani, 2023, Meyer, Wyse, and Corinth, 2023, Meyer, Wyse, Meyer, Grunwaldt, and Wu, 2024, Meyer, Wyse, and Williams, 2025, Meyer, Wyse, Meyer, Grunwaldt, and Wu, 2025). These important papers are the first to document the economic lives of homeless Americans at scale. Meyer et al. (2024) document long-term deprivation, with employment and to some extent earnings declining in the years before observed homelessness, a pattern we confirm using administrative data linked to income tax records from Ontario, another Canadian province (our BC data lack earnings records).[5] Because the economic circumstances of those who become homeless overlap so heavily with those of the housed poor, Meyer et al. (2024) conclude that predicting who will become homeless is exceptionally difficult. Our data have three features that let us identify the risk factors for homelessness and predict entry out of sample. First, we observe flows into homelessness rather than a stock at a single point in time. This lets us study first entries and precise timing of events relative to those entries. Second, our data are monthly, so we can see adverse events accumulate in the months just before entry. Third, they span broader domains including health and criminal justice, so we observe the non-economic events that most sharply distinguish those who enter homelessness.

Our work also advances the predictive models of the California Policy Lab (e.g., von Wachter, Bertrand, Pollack, Rountree, and Blackwell, 2019, Blackwell, Caprara, Rountree, Santillano, Vanderford, and Battis, 2024) and Allegheny County (Castillo, Zamorano, Jaramillo, and Gonzalo, 2020), which demonstrate that prediction of homelessness from administrative records is feasible and actionable.[6] These policy reports focus on implementation rather than on identifying the risk factors that drive prediction. Our contribution is to identify the specific risk factors for homelessness and their relative importance, and to investigate the additional predictive value of childhood history, which their data do not cover. By showing that housing instability often has roots in early life, we also contribute to the broader literature on the long-run impacts of childhood environment (e.g., Chetty and Hendren, 2018, Chyn and Katz, 2021).

2. Data

Understanding the pathways into homelessness requires data tracking individuals over time and across the multiple systems they interact with before a first homelessness spell. Our data are uniquely suited to this task: we observe monthly records spanning healthcare, education, child welfare, corrections, social assistance, and housing, allowing us to document risk factors from childhood onward.

[5] The Ontario records link social assistance and hospital data to individual tax files, and identify homelessness using two of the three measures we use in BC. They lack most of the records that make the BC data unique, including childhood events, criminal justice involvement, and detailed substance use and mental health records from outpatient and pharmaceutical care. The Ontario hospital records do, however, allow for some external validity checks against our BC findings. We describe these data in Section 2.

[6] Related work by Shinn, Greer, Bainbridge, Kwon, and Zuiderveen (2013) and Greer, Shinn, Kwon, and Zuiderveen (2016) reports on a model used to screen applicants to New York City's Homebase prevention program for shelter entry risk.

2.1 BC data

We use linked administrative data from the Canadian province of British Columbia, accessed through the province's Data Innovation Program. The data link individual-level records across multiple government systems: income and disability assistance (IA/DA); healthcare (hospital inpatient, emergency room, outpatient, pharmaceutical dispensations, and chronic disease registries); education (K-12 enrollment and graduation records); child welfare (foster care and formal supervision by the Ministry of Children and Family Development); corrections (custody discharges and criminal charges); and vital statistics (births and deaths). For those born in BC from 1986 onward and continuously present in the province, we observe their complete administrative histories, from birth through adulthood. Appendix A provides detailed information on the data sources and variable definitions.

A limitation of our BC data is the absence of employment records. We do not observe earnings or job loss directly. We do, however, observe entry into income assistance, which requires income to fall below a specified threshold. So we capture the ultimate consequence of employment instability, even if we do not observe the decline in earnings that precedes it. To measure earnings around homelessness entry, we use data from Ontario described below.

2.2 Ontario data

We complement the BC data with an independent set of Ontario administrative data. These data link social assistance to hospital and individual tax files and allow us to construct a homelessness measure similar to the one we describe for BC below.[7] The tax files provide the direct measures of earnings and income that the BC data lack, and the hospital records allow an external validity check on outcomes such as emergency room visits. The tax files end in 2019 and cover an earlier period than our BC event studies. The Ontario data cover only individuals with social assistance contact and lack most of the records that make the BC data unique, including childhood events, non-hospital medical care, and criminal justice interactions. Because of this limitation, we do not use the Ontario data for comparisons with the general population or for prediction, applications that require the full population coverage and richer set of records available in BC. Appendix D describes these data in more detail.

2.3 Measuring homelessness

Our measures of homelessness are drawn from three administrative sources. Each source captures a different type of homelessness. This composite measure provides broader cover-

[7]The Ontario data include a homelessness indicator from both social assistance and hospital records, but no shelter records.

age than any single source.

First, IA/DA records identify individuals receiving income or disability assistance who are designated as having "no fixed address" (NFA). NFA status captures individuals who are sleeping rough, staying in emergency shelters, or living in unstable arrangements, such as staying temporarily with friends or family without a permanent address to report. In accordance with provincial guidelines, we define homelessness as having NFA status for three or more consecutive months (NFA3)[8]. Shorter NFA spells may capture transitory events unrelated to actual homelessness, such as administrative errors or temporary situations in which a recipient was moving between addresses when applying for IA/DA.[9] Second, we use the Shelter and Homeless Outreach records that capture nightly shelter stays. This covers all BC Housing-affiliated emergency shelters in British Columbia from 2018 onward. Third, we identify hospital inpatients with homelessness diagnosis codes. Canadian hospitals are required to record this code whenever they become aware that a patient has no fixed address.[10] This diagnosis code has been reported since 2001.

Three features of BC's social programs make these measures unusually comprehensive. First, IA is a cash benefit of last resort available to anyone whose income and assets fall below specified thresholds. Unlike US welfare, which is largely restricted to families with children, IA is available to all household types.[11] This means the NFA flag captures individuals across all population groups, including single men who make up two-thirds of the homeless population. Second, because healthcare in Canada is almost entirely public, the hospital data covers the full population, avoiding the coverage gaps that complicate US analyses based on Medicare or Medicaid records. Third, shelter records can be linked to our administrative panel because individuals must identify themselves upon registration at a shelter, typically by presenting their BC Services Card. The matching process uses personal health number, name, sex, birth date, and postal code. Of all shelter records, 86% are successfully linked to a unique panel identifier that appears elsewhere in the data. We include the 14% that are unlinked in our homelessness counts, but because they cannot be tracked across other administrative data, we exclude them from the main analysis.

Our primary measure of homelessness, "Any Measure," flags individuals identified as

[8]We define the start date of the homelessness spell as the first month of the NFA flag.

[9]Most NFA3 recipients receive social assistance close to the minimum allowable amount, implying they report no meaningful shelter costs (see Appendix Figure E.2).

[10]This information typically emerges during patient registration or clinical interactions—for example, when recording the patient's address or taking a medical history. See Appendix A for details. Emergency departments also report a homelessness diagnosis code, but our data do not have it currently.

[11]In recent years, for example, the number of single males in receipt of IA/DA is over 40% higher than the number of lone parents (Green, Hicks, Warburton, and Warburton, 2022). In 2024, maximum IA benefits for an unattached single individual considered employable were $14,080 per year. To qualify for benefits, an applicant must have income from other sources below the maximum benefit amount and liquid assets of less than $5,000 (Laidley and Oliveira, 2025). Overall, 87.7% of our homeless sample from 2018 to 2023 were IA/DA recipients at some point in the year they were homeless.

homeless across any of the three sources. By combining these sources, we capture individuals who may appear in only one system, such as those who avoid shelters but access healthcare, or those who use shelters but do not receive income assistance. Appendix Figure E.3 illustrates the extent of this overlap within a calendar year. 43% of those identified as homeless appear only in NFA records, about one-fourth appear only in shelter records, another fourth appear in both, and only 7% appear only in hospital records.

We conduct three external validity checks of these administrative homelessness measures. First, we validate our measures against self-reports collected at Supportive Housing intake, where entrants report prior homelessness independently of our three administrative sources. Appendix Figure E.3 shows that we flag nearly three-quarters of these self-reported homeless entrants in the same calendar year. Second, Appendix Figure E.4 shows that our NFA3 measure of homelessness began rising in the mid-2010s, around the same time as the annual point-in-time street counts, although the rise is much larger in the NFA3 measure. Finally, Appendix Figure E.5 shows that NFA3 trends from our BC data align with trends from elsewhere in Canada, including nationwide and Toronto-specific point-in-time counts, and Ontario-wide estimates derived from user lists of homelessness services.

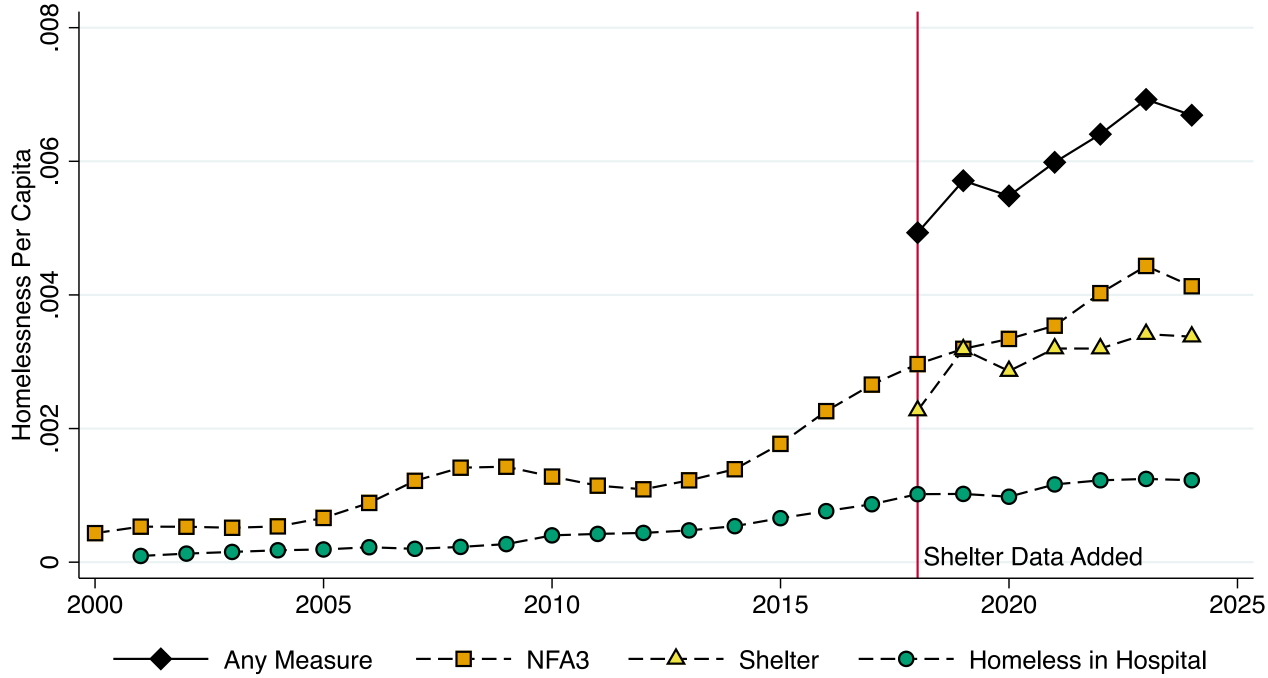
2.4 Homelessness trends

Figure 1 shows the evolution of the homeless population in British Columbia from 2000 to 2024. We present our primary measure (*Any Measure*), for the years after 2018, when our shelter data begins. We also present the NFA3 and hospital measures on their own since they provide a consistent measure from 2000 onward. Based on the NFA3 measure alone, the number of unique individuals experiencing homelessness in a given year rose by a factor of 10 between 2000 and 2024, which far exceeds population growth. When we add in the shelter data, homelessness rises to over 0.67% of the provincial population or 38,000 unique individuals. These numbers are very similar to those produced by the province (Government of British Columbia, 2024).

Figure 2 decomposes the annual stock of homeless individuals into four flows: homeless in the previous year, housed in the previous year, not observed in the province in the previous year, and non-linkable identifiers. The flow of individuals homeless in the previous year accounts for a growing share of the stock after the mid-2010s, which suggests that longer spells contribute to the rise in homelessness over the last decade. Consistent with rising duration, Appendix Figure E.6 shows that NFA spells of seven or more months per year have grown faster than short spells since 2000.

This rise in homelessness is not confined to major urban centers. While Vancouver had among the highest per capita rates in the early 2000s, many smaller cities have since sur-

Figure 1: Evolution of the Homeless Population, yearly



Note: This figure shows trends in the number of people recorded as homeless at some point during each year. The first series is "Any Measure", i.e., three consecutive months with no fixed address (NFA3), in shelter, or homeless in hospital. The other series show each component individually. The vertical line denotes 2018, when shelter data became available. All series exclude individuals with a non-linkable identifier, except for those that appear in the shelter data.

passed it, and even rural areas experienced substantial increases (Appendix Figure E.7). This geographic spread suggests that the forces driving homelessness are province-wide, and that research focused on major cities will miss a growing share of the homeless population.

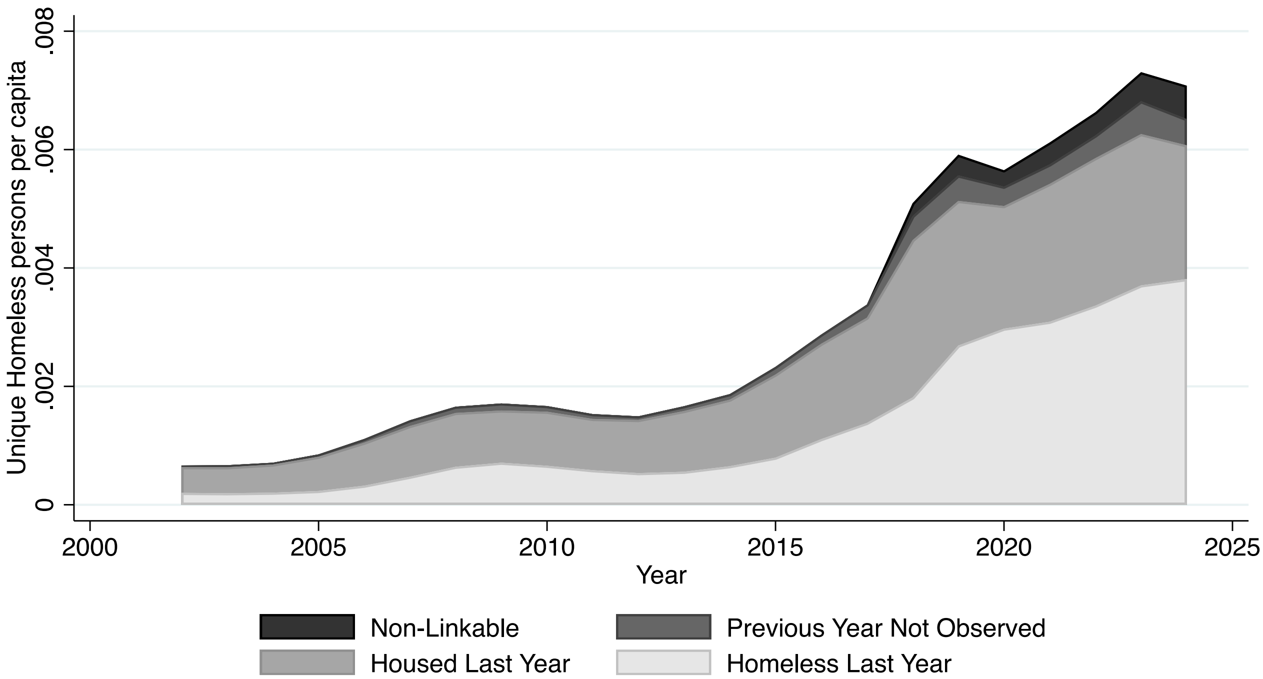
3. Characteristics of the Homeless Population

This section establishes a descriptive profile of the homeless population relative to the general and low-income housed populations. Documenting these differences helps distinguish the specific correlates of homelessness from the broader correlates of poverty.

We consider all BC residents aged 19 to 64 between 2018 and 2023. We define characteristics at the person-year level and average these characteristics over three groups: the "homeless" population; Income Assistance and Disability Assistance (IA/DA) recipients who were not classified as homeless in that year; and the "housed" population (all non-homeless residents).

Our analysis distinguishes between predetermined characteristics and adult outcomes. Predetermined characteristics include demographic attributes, child welfare interactions,

Figure 2: Decomposition of Stock of Homelessness into Annual Flows



Note: The figure decomposes the stock of "Any Homeless" in each year into individuals who (a) were also homeless last year, (b) were observed in the province last year but not homeless, (c) were not observed in the province last year, and (d) had unlinkable identifier. An example of the latter would be individuals appearing in emergency shelter records who could not be reliably matched in the Data Innovation Platform.

and educational history. These traits are either permanent or acquired prior to the observation period, so they may be risk factors for homelessness but cannot be its consequence. Documenting these childhood histories is a contribution of this paper. For these characteristics, we restrict the sample to individuals young enough to have been observed in BC administrative data during their childhood. Adult outcomes include adult histories of health, welfare, substance abuse, and interactions with the justice system. While these outcomes characterize the adult lives of the homeless population, they may be consequences of homelessness instead of risk factors. The full set of characteristics is shown in Appendix Table E.1, but we discuss notable ones below.

3.1 Predetermined Characteristics: Demographics, Childhood, and Education

Panel (a) of Figure 3 reports demographic characteristics. The homeless population is 67% male, compared to approximately 50% for both the housed and housed IA/DA populations. All three groups have similar average ages, from 40.7 to 42.7 years.[12] The homeless population has the lowest share of mothers born outside Canada at 9%. This is roughly half the rate

[12] All bar charts in this section report percentage shares, while age is reported in years.

of the housed IA/DA population and one-third that of the housed population. Similarly, the homeless population is less likely to be recent arrivals to the province (29.7%) than the housed population (43%), as measured by whether they were registered in the province before adulthood. Overall, the homeless population is similar in age[13] but more likely to be male and less likely to be immigrants than the housed population and the merely poor.

Panel (b) of Figure 3 displays childhood family stability. We find that 26% of the homeless population interacted with the foster care system between ages 12 and 17, and an additional 25% were under the supervision of the Ministry of Children and Family Development, implying that there were concerns about the child's well-being. In total, 51% of the homeless population interacted with the provincial family system during childhood, contrasting with only 4.1% for the housed population and 24.3% for the IA/DA population. Family instability is also reflected in birth records: 65% of the homeless population were born to unmarried parents.

These adverse childhood environments parallel the poor educational outcomes reported in Panel (c). 78% of the homeless population did not graduate from high school, compared with 66% of the IA/DA population and 19% of the housed population. Consistent with these low graduation rates, 47% of the homeless population had an inclusive education designation[14], similar to the IA/DA population. Appendix Table E.1 decomposes these designations and shows that homelessness relates more strongly to behavioural conditions than to physical or intellectual ones. Overall, the homeless population exhibits significant disadvantage in childhood outcomes through family instability and low human capital.

3.2 *Adult Outcomes: Health, Substance Abuse, and Criminal Justice*

We next consider whether these early disadvantages are matched by poor adult outcomes. Panel (a) of Figure 4 reports diagnosed chronic diseases. The homeless population has high rates of chronic disease, including mental illness. These rates are similar to the IA/DA population but substantially higher than the housed population. Schizophrenia is most strongly associated with homelessness, affecting 17% of the homeless population compared to 1.2% of the housed population.

Panel (b) of Figure 4 reports substance use disorder (SUD) statistics. 68% of the homeless population has been diagnosed with a chronic SUD, while 49% have recently received treatment, and 29% have recently received opioid agonist therapy.[15] These substance use rates are much higher than those of the poor but housed population. Finally, Panel (c)

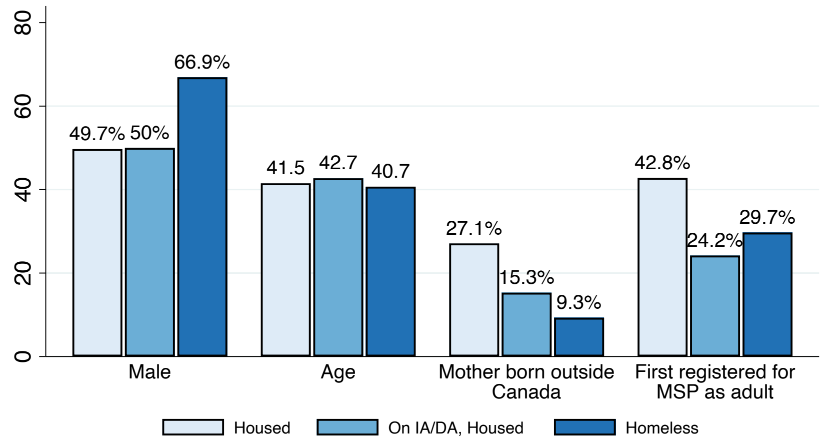
[13] Figure E.8 plots the cumulative likelihood of ever being homeless at each age.

[14] Meaning they were flagged as having some type of barrier to succeeding in school.

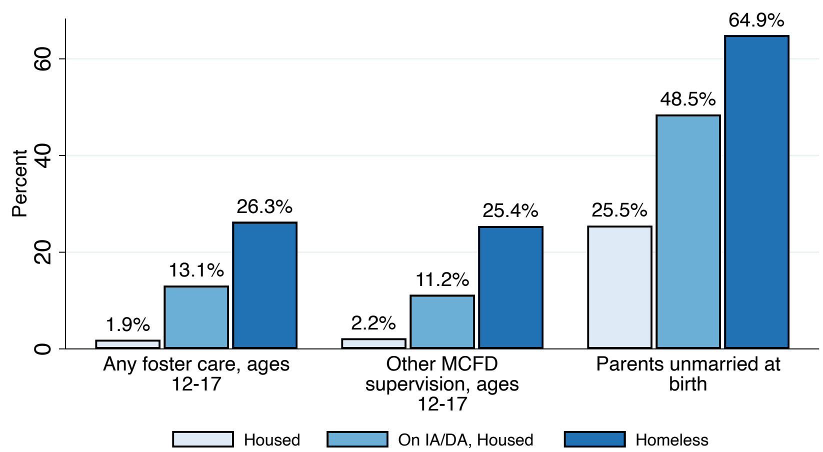
[15] Treatment refers to care in an emergency, inpatient, or outpatient setting. Opioid agonist therapy is measured separately, as medication dispensed from a community pharmacy.

Figure 3: Predetermined Characteristics: Demographics, Childhood, and Education

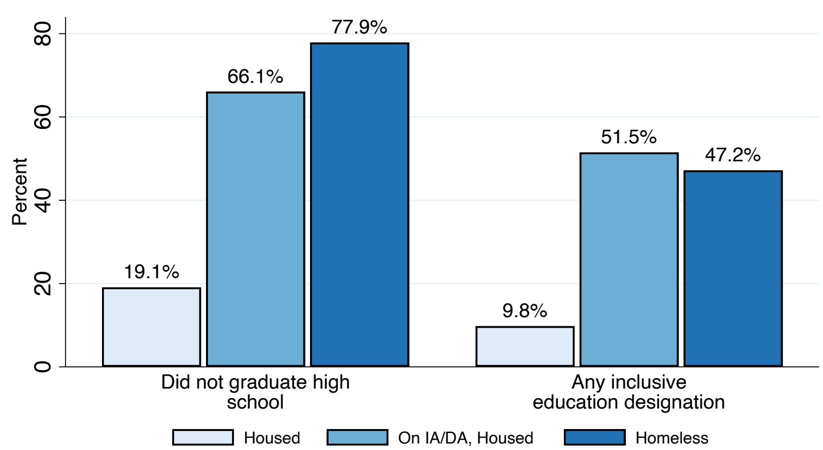
(a) Gender, Age, Immigrant Status



(b) Childhood Family Stability



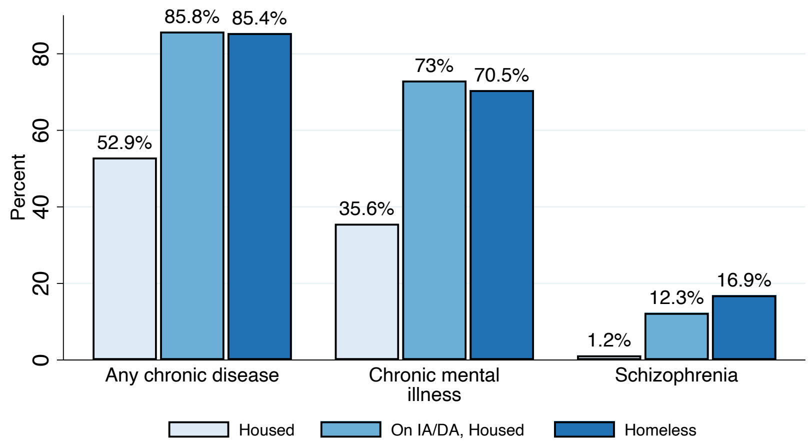
(c) Education



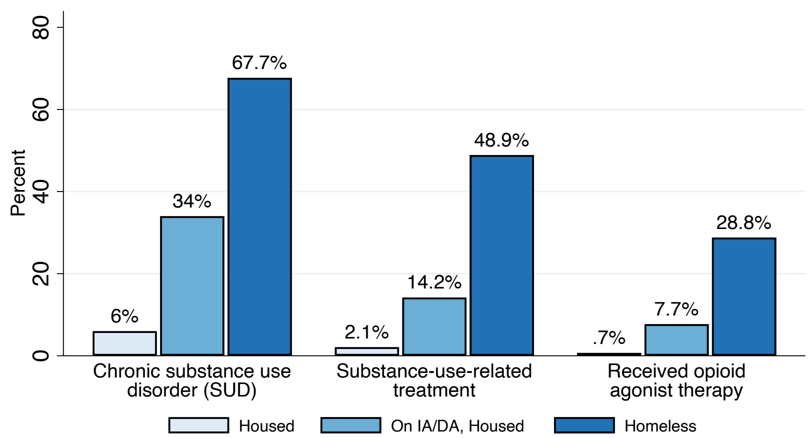
Note: The figure reports the share of adults aged 19 to 64 with each predetermined characteristic at the person-year level from 2018 to 2023, separately for three groups: (1) never homeless in that year, (2) never homeless in that year and receiving IA/DA, and (3) ever homeless in that year. 'Mother born outside Canada' and 'Parents unmarried at birth' are drawn from BC birth records and are defined only for individuals born in BC. All variables in panels (b) and (c) are restricted to cohorts born in 1986 or later who appear in BC Ministry of Education enrollment records.

Figure 4: Adult Outcomes: Health, Substance Abuse, and Criminal Justice

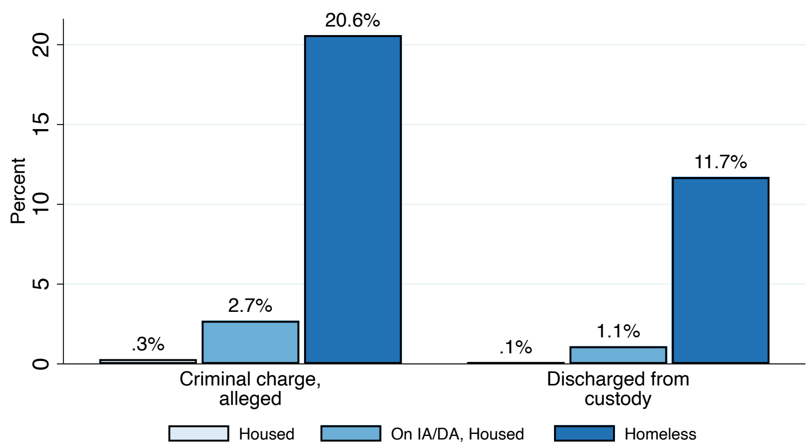
(a) Diagnosed Chronic Disease



(b) Chronic SUD and Treatment for Substance/Alcohol Problems



(c) Criminal Justice System Interactions



Note: The figure reports the share of adults aged 19-64 who experience each outcome at the person-year level from 2018 to 2023, separately for three groups: (1) never homeless in that year, (2) never homeless and receiving IA/DA, and (3) ever homeless in that year. Panel (a) uses the Chronic Disease Registry. Panel (b) reports rates of chronic substance use disorder, hospital or outpatient treatment for substance or alcohol disorders, and receipt of opioid agonist therapy. In panel (c), we report the share with at least one alleged crime, measured from criminal charges and the reported date of the alleged offence; the share discharged from custody is defined in Appendix Section A, and includes both release from pre-trial and post-trial detention.

reports interactions with the criminal justice system. These outcomes exhibit the largest gaps in our analysis. While interaction rates are very low for both housed groups, they are high for the homeless population: 20.6% are alleged to have committed a crime in a given year, and 11.7% have been released from custody.

In Appendix B, we further split the homeless population into those with short spells (under 7 homelessness months in the calendar year) and long spells (7 to 12 months). People with longer spells are more likely to be male (70% vs 65%) and more disadvantaged on almost every dimension we measure. They are less likely to have graduated from high school (19% vs 24%), more often diagnosed with a substance use disorder (73% vs 65%), and more often alleged to have committed a crime (24% vs 19%).

Overall, the homeless population is disadvantaged across all measured dimensions. We observe particularly large gaps in foster care history, high school graduation, substance abuse, and criminal justice interactions. While childhood characteristics are plausible determinants of homelessness, adult outcomes require a panel analysis to distinguish risk factors from consequences. We address this distinction in the following event studies.

4. What happens right before becoming homeless?

In this section, we describe life trajectories prior to the onset of a first homelessness spell. We track socio-economic, legal, and health outcomes for all adults (age 19-64) who first became homeless between 2018 and 2023.[16] We characterize these trajectories using two moments. The first is the likelihood, $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$, which measures the prevalence of an event within the future homeless population in a given month s relative to the month of homelessness entry ($s = 0$). At $s = -2$, for instance, this likelihood is the share of individuals experiencing the event two months prior to first entry into homelessness. We also report the Bayes factor, which measures the event's predictive power. We define the Bayes factor as the ratio of the likelihood described above for the first-time homeless population to the likelihood in the rest of the population: $\frac{E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]}{E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]}$. A high Bayes factor indicates that an event is highly diagnostic of future homelessness (even if it is rare according to the likelihood measure).

Throughout this section, the likelihoods and Bayes factors are conditional on being alive and resident in the province in month s. Appendix Figure E.10 panel (c) shows that inferred residency rises from 75% four years prior to homelessness onset to 100% in the year of

[16] Two gaps in our data could lead us to miscode a homelessness spell as a first entry. Our IA/DA sample begins in 2000, so any prior NFA spell would be missed. The homeless-in-hospital diagnosis flag, drawn from hospital inpatient records, is available since 2001, so spells relying on that flag before 2001 would also be missed. The shelter data begin only in 2018, and Figure E.3 shows that shelter-only spells account for 27 percent of homelessness spells in a given year. An individual whose pre-2018 homelessness was a shelter-only spell would be miscoded as a first-time entrant.

entry. Mortality rises steadily after entry, reaching roughly 7% within three years of entering homelessness (Figure E.10 Panel (d)). Finally, Figure E.9 shows that about 75% of first-time homeless entrants are no longer homeless 12 months later, implying that the homeless entries we study are a mix of quickly-resolved spells and long-term conditions.

Figure 5 reports event studies for alleged crimes, custody releases, income and disability assistance. Panel (a) plots the likelihood and Bayes factor for alleged criminal offences. We find a rapid rise in the likelihood of allegedly committing a crime as people approach homelessness, increasing from 1.6% four years prior to onset to 4% in the month prior. The Bayes factor rises to 51 in the month before homelessness, meaning that someone who will become homeless next month is 50 times more likely to have allegedly committed a crime in the current month than someone who will not. Alleged crimes spike further in the month of homelessness onset, but we cannot tell whether an event in that month precedes or follows onset.[17] Panel (b) reports similar patterns for discharge from custody. Like criminal charges, custody releases are highly predictive of the onset of homelessness (high Bayes factor) but occur for a relatively small share of the population in any given month (low likelihood). Panel (c) displays trends in income or disability assistance receipt. The share receiving either one rises from 35% four years before onset to 46% in the month before entry, deteriorating gradually as onset approaches without the sharp acceleration seen in alleged crime.

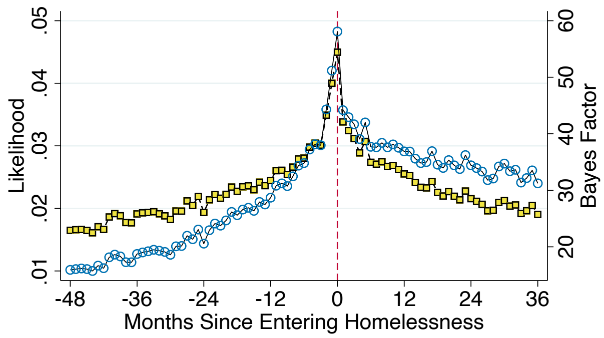
Figure 6 reports trajectories for health events: ER visits and treatment for head injury, mental health, and substance use.[18] All four outcomes show acceleration prior to onset, similar to alleged crimes. In Panel (a), the likelihood of an ER visit in a month rises from about 5% four years prior to 12% a month before onset, with a Bayes factor of 6. Like other outcomes, ER visits spike in the month of onset, reaching 23%. Panel (b) plots treatment for a head injury. It is a rare event (rising to 1.3% a month prior) with a moderate Bayes factor of 5. Panels (c) and (d) show treatments of mental health and substance-use-related issues. Receiving mental health treatment is common, with a likelihood rising from 12% four years prior to onset to 22% the month before onset (Bayes factor of 5). Receiving treatment for substance or alcohol disorders stands out as both common and highly predictive of homelessness entry. The likelihood rises from 6% four years prior to 13% a month before onset, with a Bayes factor of 15. Additional event studies in Appendix E show similar patterns for other health outcomes, such as inpatient visits and suggests that the events in Figure 6 are representative of a general increase in health problems as people approach homelessness. Appendix E report event studies for many other outcomes observed in our

[17]This is a common pattern across all our measures. Within the month of entry, we cannot observe the order of events, so we cannot tell whether a given event precedes or follows onset. A related issue is that an interaction with a government system, such as a hospital visit, can register an ongoing spell for the first time, recording it as a new onset. In the hazard model of the next section, we use a longer lag as a robustness check.

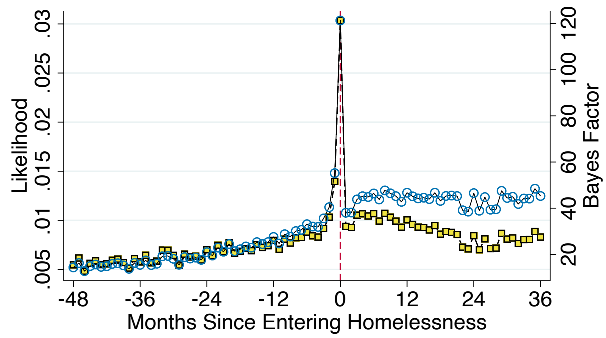
[18]This includes treatments for alcohol disorders.

Figure 5: Event Studies: Legal and Socioeconomic Outcomes

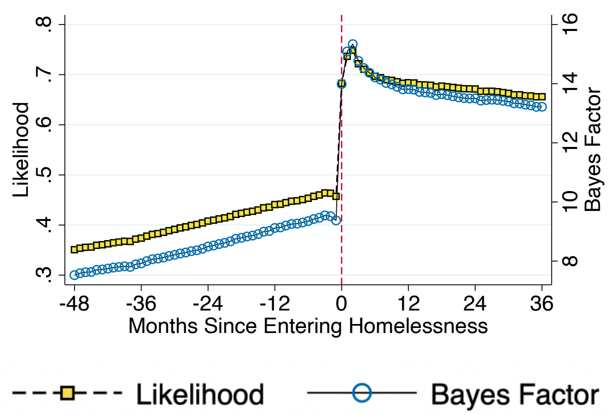
(a) Criminal Charge (Date of Alleged Offense)



(b) Discharged from Custody



(c) IA/DA Receipt

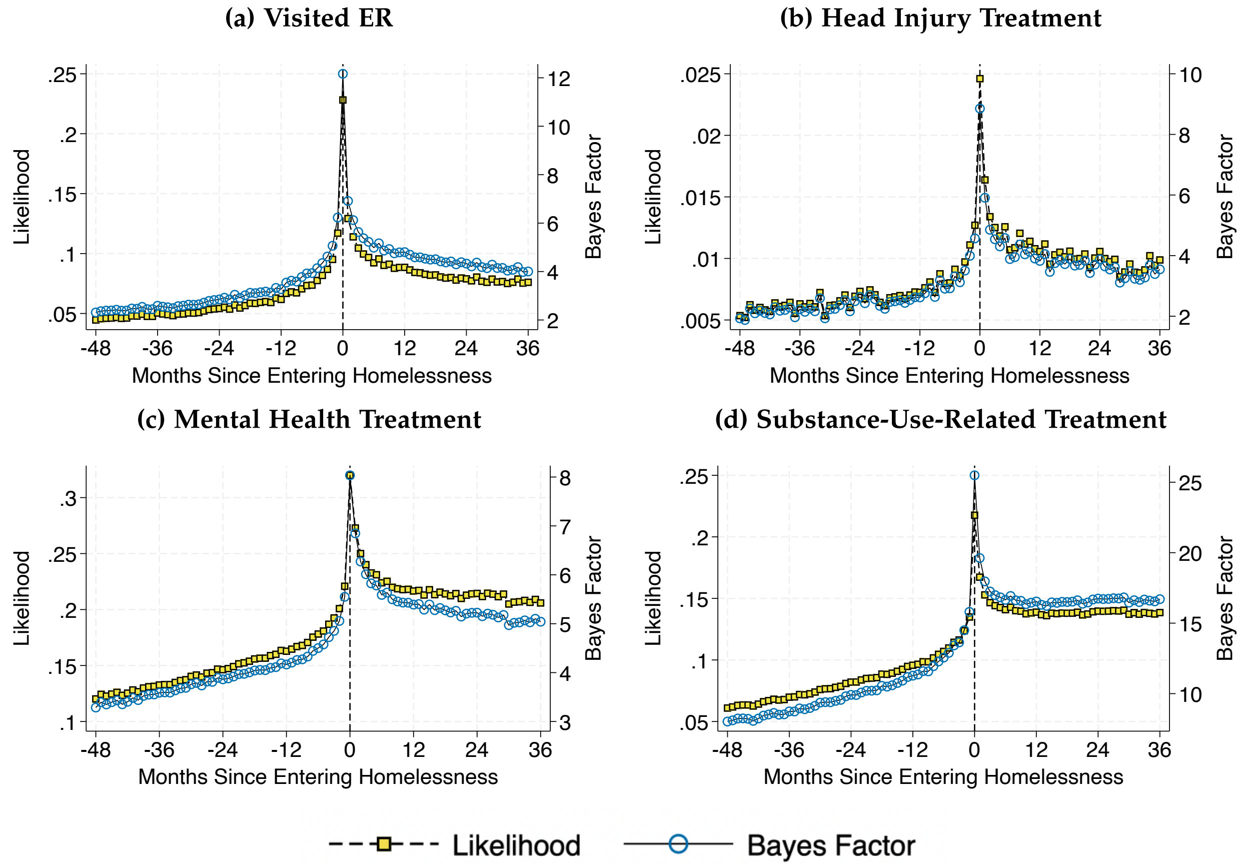


Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that homeless entrants are 15 times more likely to experience the outcome than non-entrants in event month s.

data, including, for instance, prescriptions by drug class (anti-psychotics, benzodiazepines, etc). Table E.3 summarizes all event studies, reporting the likelihood of each event in the month before entry and the associated Bayes Factor.

The event studies report each event on its own, but many future entrants experience several events over the year before onset. Appendix Figure E.14 shows that out of 20 possible adverse events spanning alleged crime, substance use, health, prescriptions, and socio-economic categories, a future entrant experiences 3 of these distinct events on average,

Figure 6: Event Studies: Health Outcomes



Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that homeless entrants are 15 times more likely to experience the outcome than non-entrants in event month s.

where repeated instances of the same event count once.[19] Appendix Table E.2 reports the underlying rates. For instance, 45% of future entrants visit an emergency room in the year before onset, and 33% receive substance use treatment.[20] Only 26% had no adverse event in

[19] Three visits to the ER, for instance, would count as one distinct event. The 20 events are: an alleged crime, being discharged from custody, ER visit, inpatient visit, treatment for substance-use-related issues, treatment for mental health, treatment for head injury, receipt of antidepressants, receipt of antipsychotics, receipt of benzodiazepines, receipt of gabapentinoids, receipt of opioids, receipt of opioid agonist therapy, receipt of pharmaceuticals for treating alcohol use disorder, a new diagnosis of substance use disorder, a new diagnosis of chronic mental illness (depression, anxiety, or other mood disorder), a new diagnosis of schizophrenia, a new diagnosis of other chronic disease, family dissolution, a new IA or DA spell. Multiple distinct events can belong to the same episode. An ER visit and an inpatient diagnosis may happen together and be recorded as two separate events, and an alleged crime and being taken into remand would count as two distinct events.

[20] Classifying adverse events into four broad categories (criminal justice interaction, substance, health, family and IA/DA), 14% of individuals had events in three or more categories and 28% in two categories in the year prior to onset.

the year before onset, falling to 12% in the onset year itself.[21]

The BC records lack direct measures of earnings and income. Appendix D addresses this limitation with the Ontario data. These data also let us replicate several of our BC event studies on an independent dataset from a province at the other end of the country, for an earlier cohort entering homelessness between 2008 and 2016. Emergency visits and income and disability assistance receipt follow the same trajectories around homelessness entry in Ontario as in BC, suggesting that our findings do not reflect BC-specific program rules, data quality, or the particular years we study. The Ontario tax records show that income and employment are low throughout. Six years before first homelessness entry, average employment earnings among tax filers are $9,400, total income is $16,200, and 51% of future entrants have any employment earnings. All three then decline steadily, reaching $4,800, $13,200, and 38% by the year before entry, before falling more sharply in the year of entry itself. Total income falls least, because government transfers partly offset the loss of earnings. These very low levels of income and job market attachment, and their gradual decline, are consistent with the long-term deprivation documented by Meyer et al. (2024). These declines in economic circumstances are slower than the acceleration in ER visits, substance use treatment, and alleged crime in the months before entry, but they reflect the same broad deterioration in life circumstances that precedes entry across all domains we study.

Overall, we find that while economic and social indicators decline gradually, criminal justice and health events accumulate rapidly immediately prior to onset. All these adverse events peak, relative to previous months, in the month just prior to onset, highlighting the acute crises that can precede homelessness entry. This pattern suggests that homelessness sometimes results from sudden adverse shocks rather than solely long-term deprivation. We do not interpret these spikes as strictly causal in isolation; a criminal charge, for instance, may be just one link in a chain of unravelling. However, these events identify distinct points of contact with government institutions—hospitals, police, and social assistance offices—that provide concrete targets for future causal investigation and early intervention. Collectively, the long-term disparities in Section 3 and the adverse events in this section imply that specific risk factors systematically precede homelessness entry. However, because these adverse events are highly correlated, it is unclear which ones carry the most risk. To isolate the most important risk factors conditional on rich individual histories, we estimate proportional hazard models.

[21] While we do not expect to predict the timing of onset accurately for someone with no adverse event in the last 12 months, we may still place them in a high-risk group. They may have a long-standing substance use disorder, an ongoing IA spell, and childhood adversity. We discuss this distinction in the next section.

5. Estimates of Homelessness Risk

In this section, we study the predictors of entry into homelessness using a model with 45 risk factors covering demographics, family circumstances, education and childhood, health, prescriptions, criminal justice, and income and disability assistance.[22] The model also includes neighborhood income decile and area-level rent. Counting each decile of childhood and current neighborhood income separately, this amounts to 61 variables, alongside year and area fixed effects.[23]

$$h_{i,\tau} = h_\tau \exp(\gamma_{\text{year}} + \gamma_{\text{area}} + \boldsymbol{\alpha z_i} + \boldsymbol{\beta x_{i\tau}}) \tag{1}$$

where $h_{i,\tau}$ is the probability that individual i becomes homeless for the first time at age τ (measured in months since the 19th birthday), conditional on never having been homeless before. The term h_τ denotes the baseline hazard: the risk of homelessness at age τ for the base group with zero values for all covariates. The covariates shift this trajectory up or down proportionally. We include calendar-year fixed effects, γ_{year}, to absorb province-wide changes that affect the risk of homelessness, and area fixed effects to absorb persistent differences in homelessness risk across areas. The vector $\boldsymbol{z_i}$ represents time-invariant characteristics, such as sex, teenage foster care placement, and high-school graduation. The vector $\boldsymbol{x_{i\tau}}$ represents time-varying risk factors. These include the 20 adverse events from Section 4, measured in the three months prior to τ, such as a new substance use diagnosis, a mental health treatment, or an alleged crime. They also include conditions established four or more months earlier, such as a longstanding diagnosis or an ongoing income assistance spell, along with current family status and neighborhood conditions. Substance use, for instance, enters in three ways: a long-standing diagnosis, a new diagnosis in the past three months, and treatment in the past three months.

We report our results as hazard ratios. For dummy variables, such as having a specific medical diagnosis, the hazard ratio is defined as $\exp(\boldsymbol{\beta})$. A hazard ratio of 2 implies that an individual with this characteristic faces double the monthly risk of becoming homeless compared to someone without it, holding all other risk factors constant.

We estimate the model on a "BC-raised" sample of individuals born in 1986 or later. This birth-year restriction ensures we observe teenage foster care history, which is recorded comprehensively starting in 1998. We also require that individuals appear consistently in administrative records during childhood and maintain continuous residency in the province

[22] A list of the variables with definitions is given in Appendix A.

[23] Area fixed effects consist of an indicator for each of BC's seven census metropolitan areas, a single indicator pooling all census agglomerations, and a single indicator pooling all rural areas.

as adults.[24] The final estimation sample consists of monthly observations for all individuals meeting these criteria from 2018 through 2022.

Appendix Table E.4 presents the full estimation results, as well as alternative specifications. In Table 1, we report hazard ratios for selected variables, including the ten with the highest hazard ratios. Column 1 ranks each variable by the magnitude of its hazard ratio amongst the 61 individual-level variables we estimate. Column 2 shows the hazard ratios. Column 3 shows hazard ratios from a more restricted model that omits all childhood and family background variables.

Panel A reports hazard ratios for events occurring in the previous three months. These recent adverse events are among the largest risk factors in our model. Allegedly committing a crime has a hazard ratio of 3.98, the highest among recent events: someone who allegedly commits a crime is nearly four times as likely to become homeless in the following month as someone who has not, all else equal. A recent diagnosis of chronic substance use disorder is the next most important event, with a hazard ratio of 3.43. Entering a new income or disability assistance spell also raises near-term risk, with hazard ratios of 2.86 and 2.49. A new chronic mental illness or schizophrenia diagnosis and an ER visit each carry ratios above 2. Substance-use-related treatment and discharge from custody fall between 1.5 and 1.75. Several other events carry hazard ratios between 1 and 1.5 and are not reported in Table 1, including mental health treatments and most prescriptions. These results are consistent with our event studies, which show a sharp rise in the prevalence of adverse events immediately before the onset of homelessness.

Panel B reports stable characteristics and established conditions present before the recent three-month window, including long-standing diagnoses and assistance spells. A substance use disorder diagnosed four or more months earlier is the highest-risk factor, at 4.56. A long-standing income assistance spell carries a hazard ratio of 3.30, and a long-standing disability assistance spell of 1.95. These large hazard ratios are consistent with homelessness following from states of pre-existing poverty. Family and social ties also matter. Being single and childless carries a hazard ratio of 2.60, being a single parent 1.93, and having parents who are deceased or out of province 1.46.[25]

Surprisingly, an increase in the median one-bedroom rent in one's area is not associated

[24]To ensure we capture childhood circumstances, individuals must appear in administrative records (e.g., school enrollment, health registry) for at least 7 of the 9 years between ages 9 and 17. To ensure we observe the risk of homelessness in adulthood, we restrict the sample to people who do not leave the province within the data period. Residence in the province is primarily defined by registration with the provincial health insurance program, which is legally required for residents. To capture the small share of residents who are not registered, we also consider a person to be a resident in month t if they were in any other administrative data within $t-3$ to $t+3$.

[25]This is relative to a base group of people who live in the same city as their parents. Appendix Table E.4 shows that people whose parents live in the province but in a different city have a hazard ratio of 1.4.

Table 1: Estimates of First Homelessness Risk Factors

Rank	Panel / Variable	Hazard Ratio	
		Baseline	No Childhood
Panel A: Recent Adverse Events (Past 3 Months)			
2	Criminal charge, alleged	3.98	4.94
3	Substance use disorder, recent diagnosis	3.43	4.67
5	Income assistance, recent spell	2.86	3.83
8	Disability assistance, recent spell	2.49	4.44
9	Chronic mental illness[a], recent diagnosis	2.20	2.42
10	Emergency room visit	2.13	2.32
11	Schizophrenia, recent diagnosis	2.05	2.03
14	Substance-use-related treatment	1.75	1.79
17	Discharged from custody	1.57	1.77
Panel B: Long-standing Conditions and Stable Characteristics			
1	Substance use disorder, long-standing diagnosis	4.56	6.49
4	Income assistance, long-standing spell	3.30	4.93
7	Household type: Single and childless	2.60	2.95
12	Disability assistance, long-standing spell	1.95	3.30
13	Household type: Single parent	1.93	2.64
15	Neighbourhood in lowest income decile	1.61	2.38
16	Chronic mental illness[a], long-standing diagnosis	1.58	1.72
18	Schizophrenia, long-standing diagnosis	1.52	1.36
20	Parents deceased or out of province	1.46	
44	Male	1.11	1.13
Panel C: Childhood & Education			
6	Did not graduate high school	2.61	
19	Parents unmarried at birth	1.52	
27	Any foster care, ages 12-17	1.32	
33	Other MCFD supervision, ages 12-17	1.26	
43	Behavioural IED	1.12	
54	Birth weight (standardized) – *not significant at 95%*	0.98	

Notes: The table reports hazard ratios from equation (1) for selected variables, estimated on a sample of BC-raised individuals from 2018 to 2022. Hazard ratios in Columns 3 and 4 represent the ratio of the probabilities of first-time homelessness for person-month observations that differ by one unit in the given covariate, all else equal. In equation 1, this is $exp(\hat{\beta})$ or $exp(\hat{\alpha})$ (α for time-invariant predictors, β for time-variant predictors). Baseline Model includes all covariates; the other model excludes childhood variables. In Column 1, "rank" orders all significant predictors ($p < 0.05$) and Birth weight by the absolute value of their coefficient — either $|\hat{\alpha}|$ or $|\hat{\beta}|$.

[a] Chronic mental illness includes depression, mood and anxiety disorders.

with a higher risk of homelessness. Given the inclusion of area fixed effects, this coefficient is identified from within-city rent changes over time, rather than rent level differences across cities. This finding is also consistent with the rise in homelessness documented in Section

2, which was largest in smaller cities and rural areas which had slower growth in rents than did major cities. Appendix Table E.5 shows that this null result is robust to using longer time periods and alternative regression specifications. Rents rose across all areas over this period, so housing costs may still have contributed through channels our city-level comparison cannot isolate.

Panel C turns to childhood and education characteristics. People who do not graduate from high school have a hazard ratio of 2.61, the sixth largest we observe. Other education and childhood outcomes are smaller but still sizeable. Having parents who were unmarried at birth, or a history of foster care during adolescence, carry hazard ratios of 1.52 and 1.32. The foster care ratio is notably smaller than the raw over-representation of former youth in care within the homeless population, which suggests it correlates with other risk factors already in the model. Other MCFD supervision and behavioural special needs in school, which Section 3 shows are common in the homeless population, carry even smaller ratios of 1.26 and 1.12, which again suggests they correlate with other risk factors. Birth weight, frequently cited as a correlate of negative outcomes later in life, is not associated with the risk of becoming homeless once other risk factors are included.

Appendix Table E.6 compares the year fixed effects from our baseline model to those from a model that includes no risk factors. Adding the risk factors moves every year effect closer to one. The 2021 effect, for instance, rises from 0.69 to 0.88. One interpretation, following Gelbach (2016), is that shifts in individual risk factors account for part of the total change in first entry into homelessness.[26] But because our hazard ratios are predictive rather than causal, we do not attempt a full accounting of how each factor contributes to year-on-year changes. Even a complete accounting need not explain changes in aggregate homelessness: in the musical chairs theory, the housing stock determines how many people become homeless, and individual factors determine only who they are (Colburn and Aldern, 2022). Our estimates may still indicate which individual-level factors are plausible candidates for explaining the rise in homelessness since the mid-2010s. For a factor to be a likely driver of the aggregate trend, it should be predictive, common, and itself trending. The five risk factors with the largest hazard ratios in Table 1 cover substance use, crime, and poverty, as measured by income assistance receipt. Crime is highly predictive but rare, and aggregate crime rates have not risen in BC since the mid-2010s (Appendix Figure E.1). Poverty is predictive and common, but poverty rates have declined (Statistics Canada, 2026), and income assistance receipt, our proxy for it, has not risen (Laidley and Oliveira, 2025). Substance use disorder, by contrast, is predictive, common, and rising rapidly over this

[26]The estimated year effects imply that per capita first entries decline from 2018 to 2019, and further during the pandemic. These year effects describe first entry among the never-homeless, not the stock of homelessness whose rise we document in Section 2. Two features of our sample period also qualify them: our risk factors do not capture pandemic-era forces, such as federal income transfers and restrictions on shelter access, and our shelter data begin in 2018, so individuals whose only earlier spells occurred in shelters appear as first-time entrants when they re-enter, which could inflate entry counts in that base year.

period (Appendix Figure E.1). Explaining the aggregate trend is beyond the scope of this paper, but among individual-level factors, substance use appears as a plausible candidate.

Researchers often lack the childhood and education records used in our baseline model. The "No childhood variables" column of Table 1 reports a restricted specification that omits them. The hazard ratios on the remaining factors rise substantially; for instance, an ongoing SUD diagnosis rises from 4.56 to 6.49. This suggests that adult outcomes capture at least some of the childhood risk. In Section 6, we return to how childhood variables affect out-of-sample prediction, along with further robustness to sample definition and estimation method.

In Appendix B, we estimate an expanded version of the model treating movements into short and long spells as competing risks. The hazard ratios and the ranking of risk factors are very similar across the two spell types.

Overall, we identify powerful risk factors across all three categories: adverse events immediately prior to onset, long-standing conditions and stable characteristics, and childhood history. We also note that the estimated hazard ratios are significantly smaller than the univariate Bayes factors reported in section 4. This attenuation highlights that adverse events are correlated. Because the proportional hazards framework is multiplicative, the combined risk for the most disadvantaged individuals is still far above the population baseline. Consider a male receiving income assistance who did not graduate high school and has a long-standing SUD diagnosis. These factors alone imply a hazard ratio above 40 relative to the rest of the population ($1.1 \times 3.3 \times 2.6 \times 4.6$), before any acute shock. A recent alleged crime would raise the combined ratio above 150. We now use this model to predict who enters homelessness, and test these predictions out of sample.

6. Predicting entry into homelessness

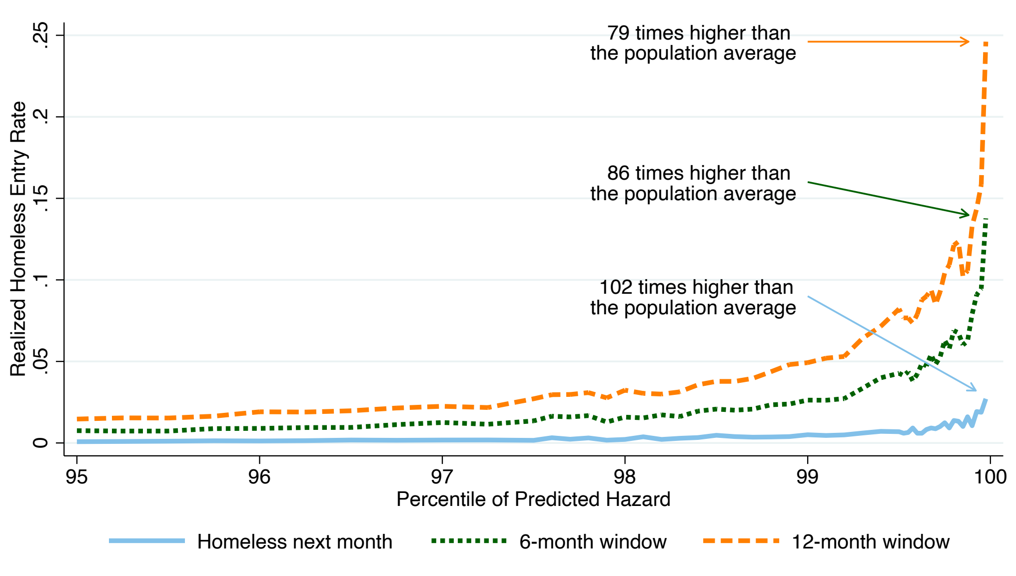
We have shown that homelessness is preceded by measurable risk factors, including adverse events immediately prior to entry. Knowing these factors can guide early intervention, and because housing support is expensive, that intervention must be targeted. In this section we use our estimated model to predict future homelessness out of sample, focusing on precision at the very top of the risk distribution.

We first predict entry into homelessness using the baseline hazard model from Section 5, re-estimated on data only through December 2022, keeping the same specification and sample restrictions. Using the estimated coefficients, we predict the monthly hazard for each person-month in 2023, conditional on the person not yet having experienced homelessness. Each prediction uses a person's history in that month, and parameters estimated strictly before the test period. This mirrors the problem facing a policymaker choosing whom to support today.

Next, we rank each person-month by its predicted hazard rate ($\hat{h}_{i,\tau}$) and divide the sample into bins, with the top bin containing 0.025 percent of the population. Within each bin, we compute the share of person-months in which the person enters homelessness over the following one, six, and twelve months. Figure 7 reports these results. Among the 0.025% of person-months with the highest predicted risk (2178 person-months), 24.6% subsequently entered homelessness within 12 months. This is 79 times the population average homeless entry rate.

Appendix Figure E.15 plots the realized against predicted entry rates by bin. Realized rates match predicted rates through most of the distribution but fall below them at the very top. The model ranks person-months correctly but overstates the risk level in the top bins.

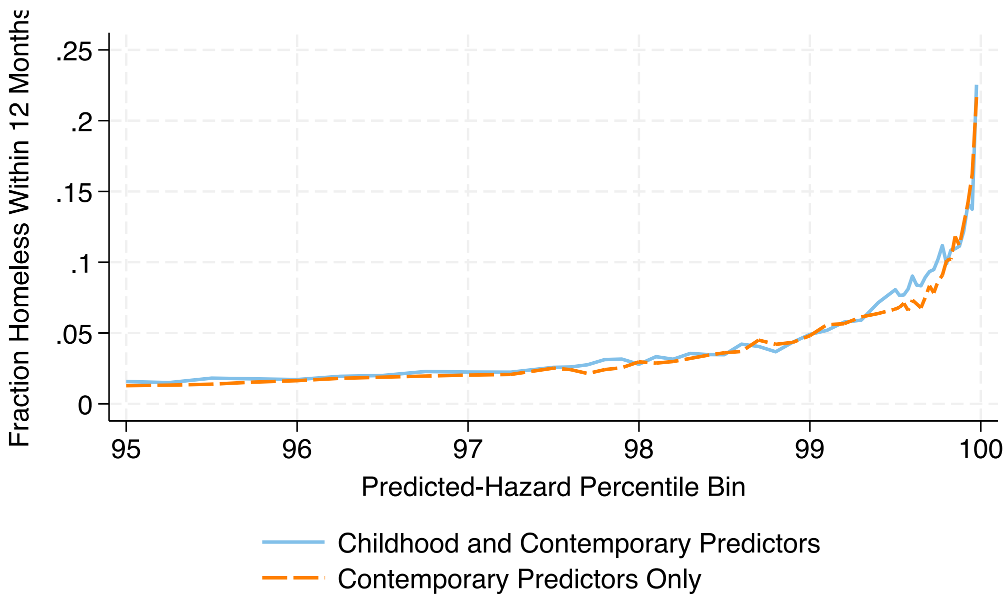
Figure 7: Out of Sample Prediction Results



Note: This figure reports out-of-sample prediction results from the Cox proportional hazard model estimated on data through December 2022 and applied to 2023–2024. Each line shows the realized hazard rate within a specified time period for each percentile bin of predicted risk (95th–100th percentiles). Bins are defined by predicted hazard percentile, with finer bins at the top of the risk distribution. The top bin contains 0.025% of the population of interest with the highest predicted hazard rate. The sample is restricted to BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. Each observation is a person-month.

Our prediction exercise emphasizes precision, but a separate question is coverage: what share of future entrants the model flags as high-risk. The top percentile of predicted risk accounts for 32% of realized first entries into homelessness (see Figure E.16), including 26% of long-spell and 35% of short-spell entries. The top three percentiles capture more than half of all entries, and the top ten capture 80%. This coverage reflects the finding in Section 4 that a large majority of new entrants experience measurable adverse events before entry. The exercise is therefore precise while still covering a broad share of the at-risk population, including those entering a long spell, a smaller but growing group captured at somewhat lower rates.

Figure 8: Prediction accuracy with and without childhood characteristics



Note: This figure reports out-of-sample prediction results comparing two specifications of the Cox proportional hazard model estimated on data through December 2022 and applied to 2023–2024: one including both childhood and contemporary predictors and one using contemporary predictors only. The sample is restricted to BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. Each observation is a person-month. The horizontal axis is the predicted hazard percentile bin, and the vertical axis is the realized first-time homeless entry rate within the subsequent 12 months. We only present the 95th–100th percentiles of the predicted risk distribution, since for lower predicted risk groups, the homelessness entry rate is near zero.

6.1 Extensions and robustness

The prediction exercise above relies on a sample of BC-born residents continuously present in the province, the month in which we date homelessness entry, and the full set of risk factors. We now show that the out-of-sample performance of our predictions holds for a broader population, survives changes to the sample and to the timing of entry, and persists when we restrict the model to smaller sets of predictors. We also show that childhood characteristics alone identify high-risk adults years in advance.

Our analysis so far has included childhood risk factors, which we observe only for individuals young enough to have been in BC since the data began. Most policy applications require predictions for the entire adult population, where such histories are unavailable. We therefore drop the childhood variables and re-estimate on the same sample. Figure 8 shows that out-of-sample performance is unchanged: the realized twelve-month entry rate tracks predicted risk almost identically with and without childhood variables. Childhood predictors add little once adult conditions are observed, because the two are highly correlated.

The redundancy of childhood and adult predictors does not mean childhood records lack predictive power on their own. We re-estimate the model using only childhood variables, the information available before any adult contact with the systems we observe. Appendix Figure E.18 reports its out-of-sample precision. The top bin has a 6% probability of entering homelessness in the next 12 months, 20 times the population rate. Characteristics fixed by age 17 therefore identify high-risk adults in any given year.

We next test whether out-of-sample performance is sensitive to the sample requirement of having continuously resided in BC since childhood. First, we include individuals who eventually left BC, following each person until the first homelessness or the first departure, whichever comes first. Predictive performance is effectively unchanged. We then expand the sample to anyone present in BC between 2017 and 2023, regardless of where or when they grew up, omitting all childhood variables. Appendix Figure E.17 shows a modest decline in precision relative to the baseline, with just under 20 percent of the highest-risk group in this extended sample entering homelessness within a year.[27]

Another concern is the timing of measured entry. As discussed in Section 2, we may in some cases observe entry into homelessness with a lag. We shift the lag structure back by one month, so that the most recent covariates used to predict entry in month τ are dated two months before τ rather than one. Appendix Figure E.17 shows that out-of-sample performance is again unchanged.

Next, we consider prediction in a setting well suited to proactive prevention: IA/DA recipients. These recipients are in monthly contact with the government, which makes intervention easier, and over 40% of first-time homeless entrants were receiving IA/DA before entry. Compared to the baseline model, prediction for this group achieves similar out-of-sample performance for the top 0.025% most at-risk and much better performance in the top 5%, where realized entry rates reach 6.5%, more than three times the baseline rate. Appendix C provides further details.

Finally, we ask whether precise prediction is possible with fewer predictors. Recall that our baseline model substantially over-predicts risk in the top bins, which is consistent with overfitting. We fit LASSO models that retain five and ten predictors, forcing in the year effects.[28] Appendix Table E.7 shows the results. Four of the top five predictors LASSO retains relate to criminal justice and substance use: a longstanding substance use disorder,

[27] The decline cannot reflect the omitted childhood variables, which barely affect precision. It more likely reflects incomplete adult histories. For individuals who spent part of their adult lives outside the province, or who were already older when our data begin, longstanding conditions such as a chronic substance use disorder predate their records in our data.

[28] We fit LASSO models with five and ten predictors, choosing the penalty at which exactly that many coefficients remain nonzero. We fix the count ourselves because predictive performance varies little across a wide range of penalties, so LASSO does not pin down a precise number of predictors.

an alleged crime, treatment for a substance use issue, and discharge from custody. The fifth is an ongoing income assistance spell. These rank 1, 2, 14, 17, and 4 by hazard ratio in our baseline model. In the top ten-factor model, three of the additional risk factors are from childhood: not graduating from high school, teenage foster care, and other MCFD supervision. In out-of-sample prediction shown in Appendix Figure E.20, the ten-predictor model performs nearly as well as the full model. The five-predictor model underpredicts the baseline model modestly between the 97th and 99th percentiles but matches it in the most at-risk bin. Overall, just a handful of predictors, drawn from substance use, criminal justice involvement, and poverty, do nearly as well as the full set, with modest additional gains from including childhood factors.

7. Conclusion

This paper documents the life trajectories leading to a first homelessness spell in British Columbia, drawing on linked administrative records spanning health, criminal justice, education, child welfare, and social assistance. We find that homelessness is the culmination of long trajectories of disadvantage. Over half of future homeless individuals had contact with the child welfare system, and fewer than a quarter graduated from high school. These childhood disadvantages are compounded by adverse events in adulthood: alleged crimes, ER visits, and substance use and mental health treatment all rise sharply in the months immediately preceding a first spell. Conditional on rich individual histories, both types of factors predict entry. Our proportional hazard model identifies a substance use disorder diagnosis, an income assistance spell, a recent alleged crime, and failure to graduate from high school as the most important risk factors. A model with just five factors, capturing substance use, criminal justice involvement, and income assistance receipt, identifies the most at-risk group nearly as well as the full model.

A key implication of our findings is that homelessness entry is predictable. Because the risk factors we identify are observed at routine points of contact with government institutions (hospitals, courts, schools, and social assistance offices), they are potentially actionable. The model identifies a highest-risk group, representing the top 0.025 percent of the population by predicted risk, that is 79 times more likely to enter homelessness than the general population. This concentration of risk makes targeted early intervention feasible and potentially cost-effective. Some of this risk is also present well before these adult contacts. Childhood records alone identify a group entering homelessness at many times the population rate, and point to a role for intervention early in life.

Our findings also speak to the limits of broad-based prevention. The province already offers income assistance to anyone in need, the kind of cash support that some US-based prevention programs are testing as an intervention. Yet homelessness has risen sharply. A broad safety net of the magnitude available in BC has not been sufficient to prevent entry for individuals facing the adverse events we document. Effective prevention may require targeted responses to these specific shocks.

References

Blackwell, B., C. Caprara, J. Rountree, R. Santillano, D. Vanderford, and C. Battis (2024, November). The Homelessness Prevention Unit: A Proactive Approach to Preventing Homelessness in Los Angeles County. Technical report, California Policy Lab.

Canadian Institute for Health Information (2022). Canadian coding standards for version 2022 ICD-10-CA and CCI. Technical report, Canadian Institute for Health Information, Ottawa, ON.

Castillo, C., M. M. Zamorano, G. Jaramillo, and S. S. Gonzalo (2020). Algorithmic impact assessment of the predictive system for risk of homelessness developed for the allegheny county. Technical report.

Chetty, R. and N. Hendren (2018). The impacts of neighborhoods on intergenerational mobility i: Childhood exposure effects. *Quarterly Journal of Economics 133*(3), 1107 – 1162.

Chyn, E. and L. F. Katz (2021). Neighborhoods matter: Assessing the evidence for place effects. *Journal of Economic Perspectives 35*(4), 197–222.

Cobb-Clark, D. A., N. Herault, R. Scutella, and Y.-P. Tseng (2016, January). A journey home: What drives how long people are homeless? *Journal of Urban Economics 91*, 57–72.

Colburn, G. and C. P. Aldern (2022). *Homelessness is a housing problem: How structural factors explain US patterns*. Univ of California Press.

Donaldson, J., L. Kandyba, and D. Wang (2026). Municipalities under pressure one year later: An update on the human and financial cost of ontario's homelessness crisis. Technical report, HelpSeeker Technologies.

Evans, W. N., J. X. Sullivan, and M. Wallskog (2016, August). The impact of homelessness prevention programs on homelessness. *Science 353*(6300), 694–699.

Gelbach, J. B. (2016). When do covariates matter? and which ones, and how much? *Journal of Labor Economics 34*(2), 509–543.

Government of British Columbia (2024). Annual estimates of the homeless population in B.C. Technical report. Accessed: 2026.

Green, D. A., J. Hicks, R. Warburton, and W. Warburton (2022). BC income assistance trends and dynamics: Descriptions and policy implications. Technical report.

Greer, A. L., M. Shinn, J. Kwon, and S. Zuiderveen (2016, March). Targeting Services to Individuals Most Likely to Enter Shelter: Evaluating the Efficiency of Homelessness Prevention. *Social Service Review 90*(1), 130–155.

Laidley, J. and T. Oliveira (2025). *Welfare in Canada, 2024*. Maytree.

McVicar, D., J. Moschion, and J. C. van Ours (2015, July). From substance use to homelessness or vice versa? *Social Science & Medicine 136-137*, 89–98.

Meyer, B. D., A. Wyse, and K. Corinth (2023, July). The Size and Census Coverage of the U.S. homeless Population. *Journal of Urban Economics 136*.

Meyer, B. D., A. Wyse, A. Grunwaldt, C. Medalia, and D. Wu (2021, May). Learning about Homelessness Using Linked Survey and Administrative Data. Working Paper.

Meyer, B. D., A. Wyse, and I. Logani (2023, November). Life and Death at the Margins of Society: The Mortality of the U.S. Homeless Population. Working Paper.

Meyer, B. D., A. Wyse, G. Meyer, A. Grunwaldt, and D. Wu (2024, April). Homelessness and the Persistence of Deprivation: Income, Employment, and Safety Net Participation. Working Paper.

Meyer, B. D., A. Wyse, G. Meyer, A. Grunwaldt, and D. Wu (2025, May). Unhoused and Mismeasured: The Accuracy of Surveys of Those Experiencing Homelessness. *AEA Papers and Proceedings 115*, 90–95.

Meyer, B. D., A. Wyse, and D. Williams (2025, April). Asylum Seekers and the Rise in Homelessness. Working Paper.

Moschion, J. and J. C. van Ours (2019, January). Do childhood experiences of parental separation lead to homelessness? *European Economic Review 111*, 211–236.

Phillips, D. C. and J. X. Sullivan (2024). Personalizing homelessness prevention: Evidence from a randomized controlled trial. *Journal of Policy Analysis and Management 43*(4), 1101–1128.

Scutella, R., G. Johnson, J. Moschion, Y.-P. Tseng, and M. Wooden (2012, July). Journeys Home Research Report No. 1: Wave 1 Findings. Technical Report 1, Melbourne Institute of Applied Economic and Social Research.

Shinn, M., A. L. Greer, J. Bainbridge, J. Kwon, and S. Zuiderveen (2013, December). Efficient targeting of homelessness prevention services for families. *American Journal of Public Health 103*(Suppl 2), S324–S330.

Statistics Canada (2026). Dimensions of poverty hub. Technical report. Accessed: 2026.

Toros, H., D. Flaming, and P. Burns (2019, March). Early Intervention to Prevent Persistent Homelessness: Predictive Models for Identifying Unemployed Workers and Young Adults who become Persistently Homeless. Technical Report 3370634, Economic Roundtable.

von Wachter, T., M. Bertrand, H. Pollack, J. Rountree, and B. Blackwell (2019, September). Predicting and Preventing Homelessness in Los Angeles. Technical report, California Policy Lab.

Wooden, M., A. Bevitt, A. Chigavazira, N. Greer, G. Johnson, E. Killackey, J. Moschion, R. Scutella, Y.-P. Tseng, and N. Watson (2012, April). Journeys Home: A Longitudinal Study of Factors Affecting Housing Stability. Melbourne.

Data Citations

- British Columbia Ministry of Social Development and Poverty Reduction [creator] (2024): BC Employment and Assistance. Data Innovation Program, Province of British Columbia. Data Extract. Approver Year 2025.
- Canadian Institute of Health Information [creator] (2025): Discharge Abstract Database Core E05. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): Health Registry and Demographics E06. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): Census Geodata E08. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): Client Roster E02. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- Ministry of Health [creator] (2025): Contiguous Client Roster E02. Data Innovation Program, Province of British Columbia [publisher](2025). Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2023): Chronic Disease Registry E03. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): Medical Services Plan (MSP) core E06. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- Canadian Institute of Health Information [creator] (2025): National Ambulatory Care Reporting System (NACRS) Core E05. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): PharmaNet Core E04. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Health [creator] (2025): BC Vital Events and Statistics E08. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Housing Corporation [creator] (2024): Shelter and Homeless Outreach Private Market Rent Supplements E06. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.

- British Columbia Housing Corporation [creator] (2024): Private Market Rent Supplements for Eligible Seniors and Working Families E06. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- BC Housing [creator] (2024): Supportive Housing E02. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Children and Family Development [creator] (2024): Child Welfare Program E07. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Public Safety and Solicitor General [creator] (2024): Corrections - Adult Community and Custody E05. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.
- British Columbia Ministry of Education [creator] (2025): K to 12 Student Demographics and Achievements E07. Data Innovation Program, Province of British Columbia [publisher] Data Extract. Approver Year 2024.

A. Data Appendix

A.1 Data Sources

This appendix provides comprehensive documentation of the administrative data sources used in our analysis. All data were accessed through British Columbia's Data Innovation Program, which links individual records across provincial government databases using consistent anonymized identifiers.

A.1.1 Income and Disability Assistance (IA/DA)

The BC Employment and Assistance records contain monthly information on all individuals receiving provincial income assistance (IA) or disability assistance (DA). These records include the assistance type, monthly payment amounts, and crucially for our purposes, whether the recipient is flagged as having "No Fixed Address" (NFA). The NFA designation is recorded by caseworkers and can be updated monthly. We use this designation as one of our primary indicators of homelessness. The BC government deemed individuals as homeless when they had three consecutive months marked NFA.

A.1.2 Health Data

Hospital Inpatient (Discharge Abstract Database)
Records for all hospital admissions, including diagnoses, length of stay, and resource intensity weights used to calculate costs. Within the ICD diagnosis codes, there is a set that identifies patients as homeless at the time of hospital admission. Hospital inpatient records are available from 2001 onward.

Medical Services Plan (MSP) Outpatient
Billing records for physician visits and outpatient services, including diagnosis codes that identify substance and alcohol use disorder treatment, mental health treatment, and head injury treatment. MSP outpatient records and treatment variables are available from 1990 onward.

Chronic Disease Registry
Provincial registry recording first diagnosis dates for chronic conditions. This includes anxiety, depression, schizophrenia, substance use disorder, and other chronic diseases. Chronic disease diagnoses are available from 1992 onward.

PharmaNet
Covers all prescriptions dispensed at community pharmacies, including the Drug Identification Numbers (DINs). We matched DINs to Anatomical Therapeutic Chemical (ATC) codes, which allows us to identify specific drug classes, such as opioids, opioid agonists, antipsychotics, antidepressants, benzodiazepines, gabapentinoids, and alcohol use disorder treatments. Pharmaceutical records are available from 2001 onward.

National Ambulatory Care Reporting System (NACRS)
Information on all emergency department visits from 2011 to 2024.

A.1.3 Housing and Homeless Shelter Data

The Shelter and Homeless Outreach records contain nightly records from emergency shelters across the province, available from 2018 onward. The Supportive Housing database records tenancies in supportive housing units, including whether tenants self-reported as homeless prior to entry.

A.1.4 Education Data

The K-12 Student Demographics and Achievement records contain annual enrollment data, graduation outcomes and Inclusive Education Designations (IEDs). IEDs are categorized as behavioural, intellectual, or physical designations. K-12 data is available from 1991. For consistency with other datasets, those graduation outcomes are available only for individuals born in 1986 or later who appear in K-12 enrollment records between ages 14 and 18. The inclusive education designation variables share the same birth-year restriction but require only any appearance in K-12 enrollment records, without the age-14-to-18 window.

A.1.5 Ministry of Child and Family Development

The Ministry of Children and Family Development (MCFD) data begin in 1996. It includes a complete listing (by month) of children and youth under the supervision of MCFD, by court order or by agreement with the parents. We distinguish between foster care placements and other MCFD supervision. We focus on experiences during adolescence (ages 12-17), as these records are most complete for our analysis cohort.

A.1.6 Corrections Data

BC Corrections data include records of provincial custody discharges from 2001 to 2024. Federal penitentiary discharges are excluded. The movements file records the dates of exit from custody, along with the reasons for movement (e.g., "Released to Parole," "Sentence/Supervision End," "Released at Court"). We also observe criminal charges, often with the date of the alleged criminal offence. For alleged offences, records missing an offence date are dropped.

A.1.7 Demographics and Vital Statistics

The MSP Client Roster provides demographic information, including sex, date of birth, and residential location at the 3-digit postal code level. The MSP contract structure allows us to infer family composition (single, coupled, with/without children). We infer an immigrant indicator based on the age at which an individual first appears in the data. This indicator is only defined for individuals younger than 50, to ensure that those who were residing in the province prior to age 18 would have been observable in administrative records at the time. Demographic variables derived from the MSP Client Roster are available from 1999 onward.

The BC Vital Events database provides birth records (for those born in BC from 1986 onward), including the parents' marital status at birth and birth weight, as well as death records for those who died in BC. Birth records also indicate whether the mother was born outside Canada.

A.2 Defining Homelessness

We construct several homelessness measures from our administrative data:

1. **NFA3**: Appearing with no fixed address for three or more consecutive months. This is the provincial government's preferred definition for the use of NFA to identify homelessness.
2. **Shelter**: Appearing in emergency shelter records for at least one night.
3. **Homeless Hospital**: Appearing as a hospital inpatient with a homelessness diagnosis code. Hospitals in Canada are required to assign the ICD code for homelessness whenever a patient's housing status is documented in their records. This information typically emerges during patient registration or clinical interactions—for example, when recording the patient's address or taking a medical history. The Canadian Coding Standards mandate this coding practice (Canadian Institute for Health Information, 2022, p. 626–627). Homelessness is defined according to the Canadian Observatory on Homelessness criteria: unsheltered, emergency sheltered, or provisionally accommodated.
4. **Any Measure**: NFA3, In Shelter, or Homeless Hospital. This is our main homelessness measure.

The BC government's preferred measure classifies a person as homeless if they meet either the NFA3 definition or the shelter definition. Under NFA3, homelessness is recorded only from the third month of the spell.

A.3 Sample Construction

A.3.1 Main Descriptive Analysis Sample

For descriptive analyses of section 3, we use all adults aged 19-64 observed in administrative data from 2018-2023. An observation is a person-year pair. Individuals are classified as homeless if they meet any homelessness definition at any point during the year. We exclude individuals with non-linkable study identifiers.

A.3.2 Hazard Model and Prediction Exercise

For hazard model of section 5, we restrict to individuals who:

- Were born in 1986 or later
- Appeared in enrollment records or MSP Client Roster for at least 7 years between the ages of 9 and 17 ("Raised in BC")
- Were continuously present in BC from age 19 until December 2023 or first homelessness, whichever came first

Continuous presence is defined as appearing in the MSP Client Roster or any administrative dataset. For non-roster appearances, we impute presence for three months before and after the observation.

A.4 Variable Definitions

Table A.1: Variable Definitions

Variable	Description	Category	Coverage
Childhood Neighbourhood Decile	Mode of neighbourhood income decile from ages 9-17.	Childhood	1986–2024
Parents unmarried at Birth	From birth records.	Childhood	1986–2024
Age of Mother at Birth	From birth records.	Childhood	1986–2024

Note: Regression analyses use the sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in the variable definitions above.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Birth Weight	Standardized to mean 0 and standard deviation 1. From birth records.	Childhood	1986–2024
Foster Care Teen	Any foster care between ages 12–17.	Childhood	1986–2024
Other MCFD Supervision	Under the supervision of MCFD by a court order or by agreement with the parents, ages 12–17. Excludes foster care.	Childhood	1986–2024
Family Received IA/DA, ages 12-17	From IA/DA records.	Childhood	1986–2024
Did not Graduate High School	From K12 records.	Education	1986–2024
Inclusive Education Designation: Behavioural	Any behavioural IED in K12 enrollment records.	Education	1986–2024
Inclusive Education Designation: Intellectual	Any intellectual IED in K12 enrollment records.	Education	1986–2024
Inclusive Education Designation: Physical	Any physical IED in K12 enrollment records.	Education	1986–2024
Any Inclusive Education Designation	Any behavioural, intellectual or physical IED in K12 enrollment records.	Education	1986–2024
Criminal Charge, Alleged	Received criminal charge leading to BC Corrections supervision/involvement. Fines and other charges without conditions to report are excluded. We associate the alleged offence with the "offence_date" recorded in BC corrections records; records that are missing an "offence_date" are dropped.	Corrections	2001-2024
Discharged from Any Custody	Appeared in the BC Corrections movements files with one of the following movement reasons: 'Released to Parole', 'Sentence/Supervision End', 'Released at Court', 'Released to Bail', 'Released to Conditional Sentence', 'Remandee Released-Time Served'. Individuals with custody group code "FED" are excluded.	Corrections	2001-2024
Male	Drawn from MSP client roster demographics file (or IA, shelter, or supportive housing records if missing)	Demographics	1999-2024

Note: Regression analyses use the sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in the variable definitions above.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Single	No spouse present on MSP contract. Inferred from MSP contract	Demographics	1999-2024
Childless in a Couple	Inferred from MSP contract	Demographics	1999-2024
Parent in a Couple	Inferred from MSP contract	Demographics	1999-2024
Single and Childless	Inferred from MSP contract	Demographics	1999-2024
Single Parent	Inferred from MSP contract	Demographics	1999-2024
Unknown Family Type	Based on MSP contract	Demographics	1999-2024
Mother Born Outside Canada	From birth records.	Demographics	1986–2024
Immigrant	First registered on an MSP contract at age 18 or older.	Demographics	1999-2024
Age	Based on birth date in MSP client roster demographics file (or IA/shelter/supportive housing data if missing)	Demographics	1999-2024
Received DA	From SDPR records	Gov't Support	2000–2024
Received IA	From SDPR records	Gov't Support	2000–2024
Dollars of IA/DA Received	From SDPR records	Gov't Support	2000–2024
Disability Assistance, Recent Spell	Indicator for being in the first three months of a DA spell. *Spells* are defined as consecutive months of DA receipt.	Gov't Support	2000–2024
Disability Assistance, Long-Standing Spell	Indicator for being in a DA spell that has lasted four or more months at the time of observation.	Gov't Support	2000–2024
Income Assistance, Recent Spell	Indicator for being in the first three months of an IA spell. *Spells* are defined as consecutive months of IA receipt.	Gov't Support	2000–2024
Income Assistance, Long-Standing Spell	Indicator for being in a IA spell that has lasted four or more months at the time of observation.	Gov't Support	2000–2024
CMA/CA/Rural FEs	Indicators for each census metropolitan area/census agglomeration. Another indicator for regions not designated as CMA or CA. Another indicator for "region unknown".	Geography	1986-2024

Note: Regression analyses use the sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in the variable definitions above.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Neighbourhood Income Decile	Neighbourhood income decile	Geography	2016-2021
Location of Parents	Indicators for individuals whose parents live in the same city as them; in a different city, but still in BC; or are deceased or out of province. "Parents" are identified as any adults on the individual's MSP contract from ages 14-16 who were 14 or more years older than them.	Geography	1990–2024
Median Rent	Within CMA/CA. Calculated from CMHC data for 1-Bedroom apartments. Inflation-adjusted and standardized.	Rental	2000-2024
Chronic Mental Illness	Ever diagnosed with depression, anxiety, or another mood disorder, as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2024
Schizophrenia	Ever diagnosed with schizophrenia as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2024
Chronic Substance Use Disorder	Ever diagnosed with substance use disorder as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2024
Any Chronic Disease	Used only in descriptive statistics. Ever diagnosed with any chronic disease as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2024
Other Chronic Disease	Used only in regression. Ever diagnosed with any chronic disease other than anxiety, depression, schizophrenia, or substance use disorder, as of current month. Based on the first diagnosis date in the chronic disease registry.	Health	1992-2024
Treated for substance-use-related issue	Appeared in MSP, ER or inpatient records with ICD9 code starting in 291, 292, 303, 304, or 305; or with ICD10 code starting in F10-F19 or F55.	Health	1990-2024
Treated for Mental Health Diagnosis	Appeared in MSP, ER or inpatient records with diagnosis ICD9 code starting in 290-319; or with ICD10 code starting in F.	Health	1990-2024

Note: Regression analyses use the sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in the variable definitions above.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Treated for Head Injury	Appeared in MSP, ER or inpatient records with ICD9 code starting in 800, 801, 803, 804, 850-854, 870-873 or 959; or with ICD10 code starting in S00, S01, or S03-S09.	Health	1990-2024
Received Inpatient Care	Appeared in the hospital discharge abstract database.	Health	2001-2024
Visited Emergency Room	Appeared in National Ambulatory Care Reporting System	Health	2011-2024
Received MSP-billed care	Appeared in MSP treatment records	Health	1990-2024
Government Healthcare Cost	Sum of inpatient, emergency room, MSP-billed care, and pharmacare costs	Health	2001-2024
Hospital Inpatient Costs	Product of resource intensity weighting and cost per weighted case	Health	2001-2024
Pharmaceutical Costs	Total pharmaceutical costs associated with dispensations in the year	Health	2001-2024
Received Alcohol Use Disorder Treatment	Identified by matching DIN to drugs with ATC code N07BB. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2024
Received Antidepressant	Identified by matching DIN to ATC code N06A. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2024
Received Antipsychotic	Identified by matching DIN to ATC code N05A. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2024
Received Benzodiazepine	Identified by matching DIN to ATC codes N05BA, N05CD and N03AE. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2024
Received Gabapentinoid	Identified by matching DIN to ATC code N02BF. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2024
Received Opioid	Identified by matching DIN to ATC codes N02A, R05DA and R05FA. No corresponding PINs. Opioid anesthetics (N01AH) are not included.	Prescriptions	2001-2024

Note: Regression analyses use the sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in the variable definitions above.

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Received Opioid Agonist	Identified by DINs and PINs that are specific to OAT.	Prescriptions	2001-2024
Resident	Appeared in any administrative data file during the year.	Other	1986-2024
Dead	Month of observation is later than or equal to the month of death recorded in vital statistics.	Other	1985-2024

Note: Many of the variables presented in this table are not observed for the full population of BC. Section A.1 describes the sources of each information and its underlying sample restriction. Regression analyses use further sample restriction described in Appendix A.3.2, which in some cases supersedes the conditions described in Section A.1.

B. Short vs Long Homelessness Spell

We sometimes distinguish between short homelessness spells, defined as fewer than seven consecutive months in a year, and long spells, defined as seven or more consecutive months. This appendix replicates the main descriptive results from Sections 3 separately for these two groups. Our objective is to assess whether the risk factors associated with homelessness entry differ systematically by spell length.

B.1 Characteristics of the Homeless Population by Spell Length

Figure B.1 replicates Figure 3 separately for short- and long-spell homelessness. Panel (a) shows that individuals in long homelessness spells are more likely to be male (70% vs. 65%) and somewhat less likely to have been recent arrivals to the province. Age and immigrant status are similar across the two groups.

Panel (b) shows that childhood family instability is more prevalent among those in long spells. The share who had any foster care between ages 12 and 17 is 30% for the long-spell homeless, compared to 24% for the short-spell homeless. The share under other MCFD supervision is similarly higher (28% vs. 24%), and the share with parents married at birth is lower (33% vs. 36%).

Panel (c) shows that educational disadvantage is also more pronounced for the long-spell homeless. Only 19% of the long-spell homeless graduated from high school, compared to 24% of the short-spell homeless. The share with any inclusive education designation is higher among the long-spell homeless (51% vs. 45%). Figure B.2 reports the three designation types separately. The gap is largest for behavioural designations (40% for long spells vs. 35% for short spells), as in Section 3.

Figure B.3 replicates Figure 4 by spell length. Panel (a) shows that the long-spell homeless are more likely to have any chronic disease (89% vs. 83%) and more likely to have a chronic mental illness (73% vs. 69%) and have slightly higher rates of schizophrenia diagnoses (18% vs. 17%).

The gaps in substance use are more pronounced. Panel (b) shows that 73% of the long-spell homeless have a chronic substance use disorder diagnosis, compared to 65% of the short-spell homeless. The long-spell homeless are also more likely to have received opioid agonist therapy (35% vs. 26%).

Panel (c) shows the largest differences across spell length. The long-spell homeless are alleged to have committed a crime at a rate of 24%, compared to 19% for the short-spell homeless. The share discharged from custody is 14% for the long-spell homeless versus 10% for the short-spell homeless. Overall, the long-spell homeless face more severe adverse events across every domain we observe. The gaps are widest for substance use and criminal justice, the same domains that most separate the homeless from the housed.

B.2 Competing Risks Models by Spell Length

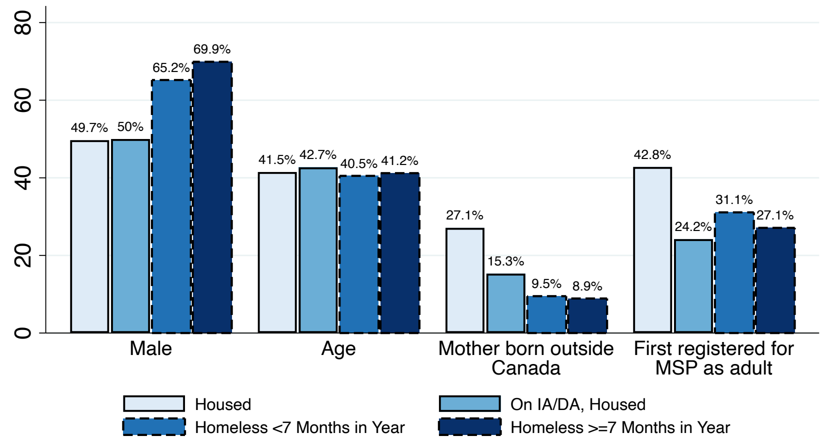
We use a competing risk model. We split first-time homelessness entries into two mutually exclusive failure events: entry into a short spell (under 7 consecutive months) and entry into a long spell (7 or more consecutive months). We estimate separate hazard models for each failure event. In both models, an individual leaves the risk set upon experiencing either type of homelessness entry, regardless of which type the model is estimating. Individuals also exit the risk set if they leave the province. The two columns of Table B.1 therefore report how each risk factor differentially predicts the onset of short versus long spells, conditional on remaining at risk of both. The ranking in Column 1 is based on the hazard ratio in the short-spell model.

The hazard ratios and rankings in Table B.1 are similar across the short- and long-spell models, and similar to the baseline estimates in Table 1. The top risk factors (a long-standing substance use disorder, an alleged crime, income assistance receipt, and failure to graduate from high school) retain large hazard ratios in both models. The clearest difference is that health conditions tend to predict short spells more strongly, with a long-standing substance use disorder at 4.87 versus 3.84 and a recent schizophrenia diagnosis at 2.27 versus 1.20. A long-standing income assistance spell predicts long spells more strongly (4.82 versus 2.89), as does not graduating from high school (2.81 versus 2.52). Overall, the same risk factors precede entry into both spell types.

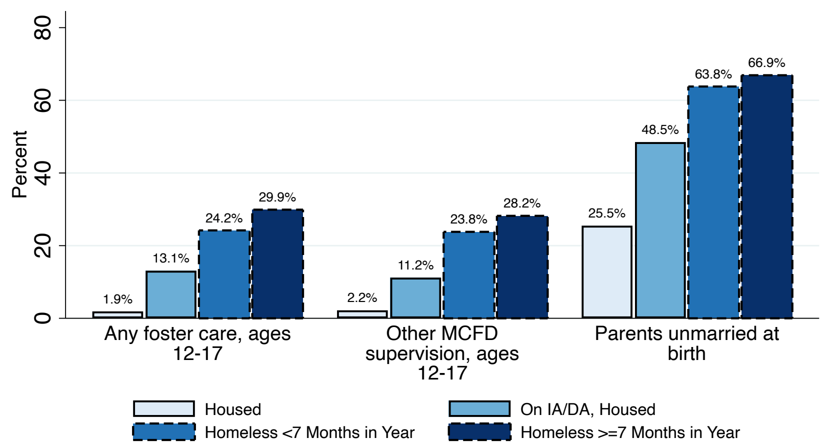
Figure B.4 reports out-of-sample prediction results separately for short- and long-spell entrants. Panel (a) shows that the realized twelve-month entry rate rises steeply at the top of the predicted-hazard distribution for both spell types. The difference in level reflects that long spells are rarer in the population. Panel (b) rescales these entry rates by the population base rate for each spell type, and shows that the top predicted risk bins are 69 times more likely to enter a long spell in the next 12 months and 81 times more likely to enter a short spell than the general population.

Figure B.1: Demographics, Childhood, and Education – Long vs Short Spells

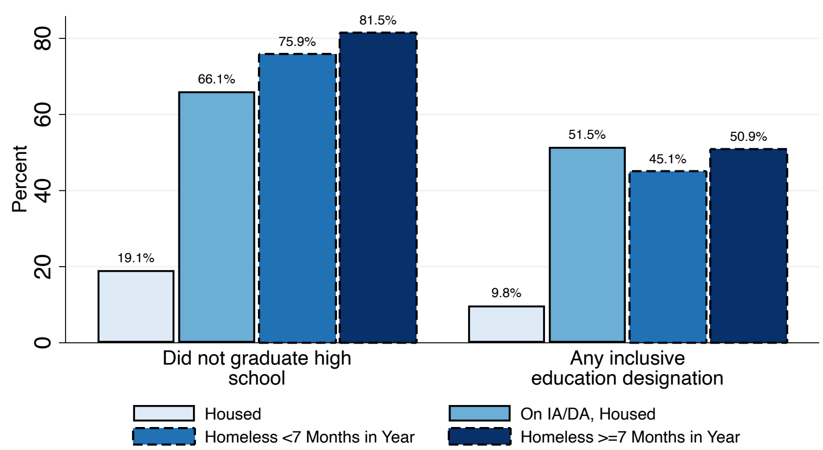
(a) Gender, Age, Immigrant Status



(b) Childhood Family Stability

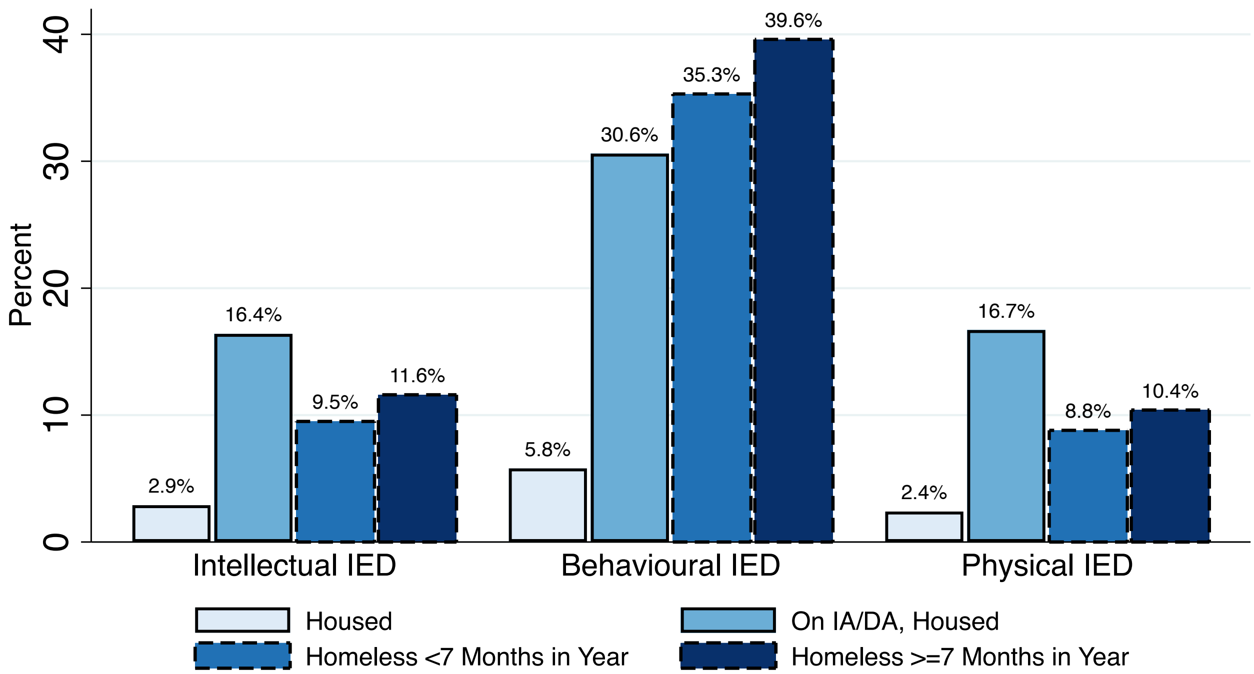


(c) Education



Note: The share of adults aged 19 to 64 with each predetermined characteristic at the person-year level from 2018 to 2023, separately for four groups: (1) never homeless in that year, (2) never homeless in that year and receiving IA/DA, we then divide the homeless group into (3) in a short homeless spells and (4) in a long homeless spells. 'Mother born outside Canada' and 'Parents unmarried at birth' are drawn from BC birth records and are defined only for individuals born in BC. All other variables in panels (b) and (c) are restricted to cohorts born in 1986 or later who appear in BC Ministry of Education enrollment records.

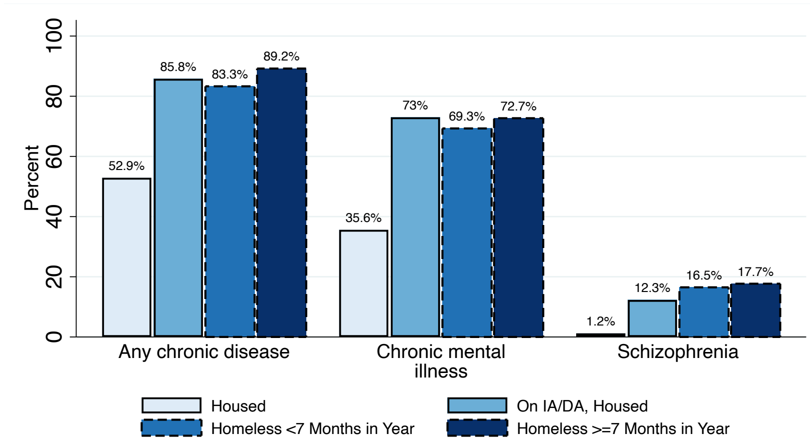
Figure B.2: Inclusive Education Designations in Childhood, by Housing Status – Long vs Short Spells



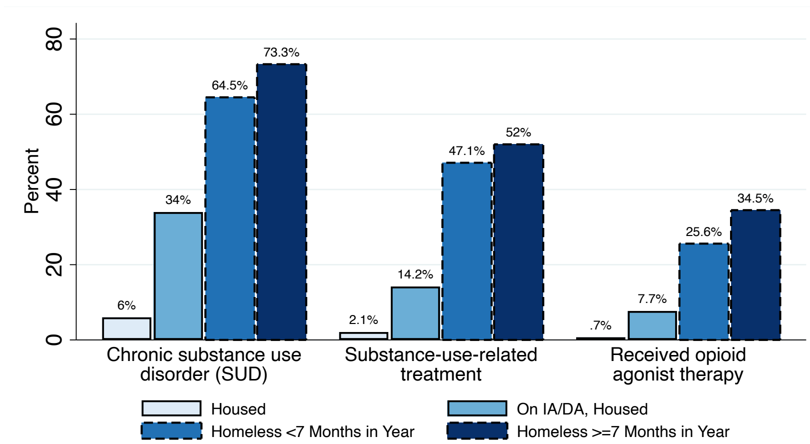
Note: Proportion of adults (19-64) who had an inclusive education designation (IED) in childhood, by person-year housing status. The housing-status groups are: (1) never homeless in that year, (2) never homeless in that year and receiving IA/DA, we then divide the homeless group into (3) in a short homeless spells and (4) in a long homeless spells. Variables are conditional on being born in 1986 or later, and on appearing in the BC Ministry of Education enrollment records.

Figure B.3: Adult Health, Substance Abuse, and Criminal Justice – Long vs Short Spells

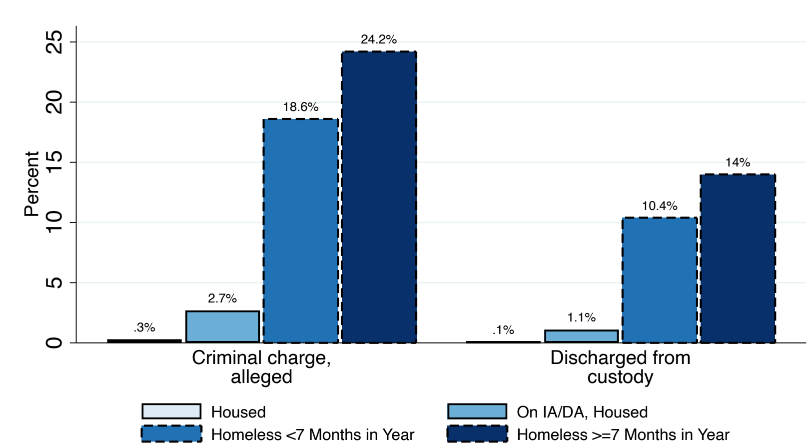
(a) Diagnosed Chronic Disease



(b) Chronic SUD and Treatment for Substance/Alcohol Problems



(c) Criminal Justice System Interactions



Note: Share of adults (19-64) who experience each outcome at the person-year level from 2018 to 2023, separately for four groups: (1) never homeless in that year, (2) never homeless in that year and receiving IA/DA, (3) in a short homeless spells, and (4) in a long homeless spells. Panel (a) uses the Chronic Disease Registry. Panel (b) reports rates of chronic substance use disorder, hospital or outpatient treatment for substance or alcohol disorders, and receipt of opioid agonist therapy. Panel (c) shows the share with an alleged crime, measured from the reported date of the alleged offence on the criminal charge; the share discharged from custody is defined in Appendix A, and includes both release from pre-trial and post-trial detention.

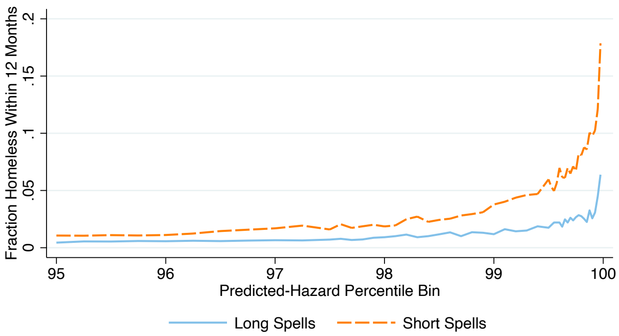
Table B.1: Competing Risk Model

Rank	Panel / Variable	Hazard Ratio	
		Short Spell	Long Spell
Panel A: Recent Adverse Events (Past 3 Months)			
2	Criminal charge, alleged	3.95	4.10
3	Substance use disorder, recent diagnosis	3.47	3.43
5	Income assistance, recent spell	2.79	2.82
8	Schizophrenia, recent diagnosis	2.27	1.20
9	Emergency room visit	2.23	1.88
10	Chronic mental illness, recent diagnosis	2.13	2.41
12	Substance-use-related treatment	1.84	1.45
20	Discharged from custody	1.49	1.83
Panel B: Long-standing Conditions and Stable Characteristics			
1	Substance use disorder, long-standing diagnosis	4.87	3.84
4	Income assistance, long-standing spell	2.89	4.82
6	Household type: Single and childless	2.79	2.17
11	Household type: Single parent	2.10	1.56
13	Chronic mental illness, long-standing diagnosis	1.64	1.44
14	Schizophrenia, long-standing diagnosis	1.62	1.31
15	Childless couple	1.62	1.05
21	Parents deceased or out of province	1.43	1.53
43	Male	1.13	1.07
Panel C: Childhood & Education			
7	Did not graduate high school	2.52	2.81
18	Parents unmarried at birth	1.52	1.53
27	Other MCFD supervision, ages 12-17	1.30	1.17
31	Any foster care, ages 12-17	1.28	1.44
47	Birth weight (standardized)	0.99	0.97

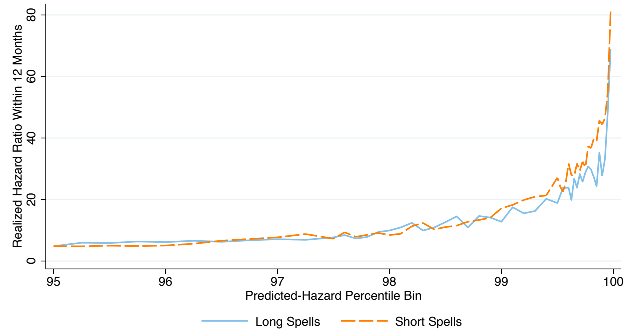
Notes: The table reports hazard ratios from equation (1) for selected variables, estimated on a sample of BC-raised individuals from 2018 to 2022. Hazard ratios in Columns 3 and 4 represent the ratio of the probabilities of first-time homelessness for person-month observations that differ by one unit in the given covariate, all else equal. In equation 1, this is $exp(\hat{\beta})$ or $exp(\hat{\alpha})$ (α for time-invariant predictors, β for time-variant predictors). Each model explains the first-time probability of entry into a short (less than 7 months) or long (7 months or more) homelessness spell. In Column 1, "rank" orders all significant predictors ($p < 0.05$) by the absolute value of their coefficient in the short spell model— either $|\hat{\alpha}|$ or $|\hat{\beta}|$.

Figure B.4: Out of Sample Prediction Results – Long vs Short Spells

(a) Hazard



(b) Hazard Ratio



Note: This figure reports out-of-sample prediction results for the competing-risk Cox proportional hazard model estimated on data through December 2022 and applied to 2023–2024. Panel (a) presents the realized first-time entry rate into short or long homelessness spells within the subsequent 12 months; Panel (b) rescales the realized entry rate by the number of short- or long- spell entries in the full population. The horizontal axis is the predicted hazard percentile bin. The sample is restricted to BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. Each observation is a person-month. We only present the 95th–100th percentiles of the predicted risk distribution, since for lower predicted risk groups, the homelessness entry rate is near zero.

C. Predicting Homelessness Entry Among IA/DA Recipients

One practical approach to outreach is to engage people who are already receiving government services. IA/DA recipients are a large group of vulnerable individuals in regular contact with the province, so we estimate a hazard model predicting their entry into homelessness. The model takes the form:

$$h_{i,s} = h_s \exp(\gamma_{\text{year}} + \gamma_{\text{area}} + \boldsymbol{\alpha z_i} + \boldsymbol{\beta x_{is}}) \tag{C.1}$$

where $h_{i,s}$ is the probability that individual i becomes homeless s months after beginning an IA/DA spell, conditional on never having become homeless earlier in that spell and still being in an IA/DA spell (as defined below) at time s. Unlike our baseline model, which studies first-ever entry into homelessness, this model studies first entry within a given IA/DA spell among individuals who may have been homeless previously. The term h_s denotes the baseline hazard: the risk of homelessness at spell length s for the base group with zero values for all covariates. The terms γ_{year}, $\boldsymbol{z_i}$, and $\boldsymbol{x_{is}}$ are defined similarly to those in our baseline model (see Section 5). Many IA/DA recipients were not present in BC during childhood, and thus lack complete education, foster care, and other childhood records. We therefore include only contemporary covariates.

The sample includes all IA/DA spells that were underway at any point between 2018 and 2023. For spells that began before 2018, we include only months within our sample period. We restrict the analysis to individuals who were not homeless at the start of their IA/DA spell. Whereas our baseline model implicitly accounts for age through the baseline hazard term (h_τ in equation 1), here we include age at entry into IA/DA as a covariate.

An IA/DA spell is defined as beginning in month t when an individual did not receive benefits in $t-1$, $t-2$ or $t-3$. The spell ends when the individual does not receive benefits for three consecutive months.

D. Replication and Extension Using Ontario Administrative and Tax Data

To assess whether the patterns documented in our main analysis are specific to British Columbia, and to extend them to income measures our BC data lacks, we use an independent set of Ontario administrative records, accessed through a Statistics Canada Research Data Centre.

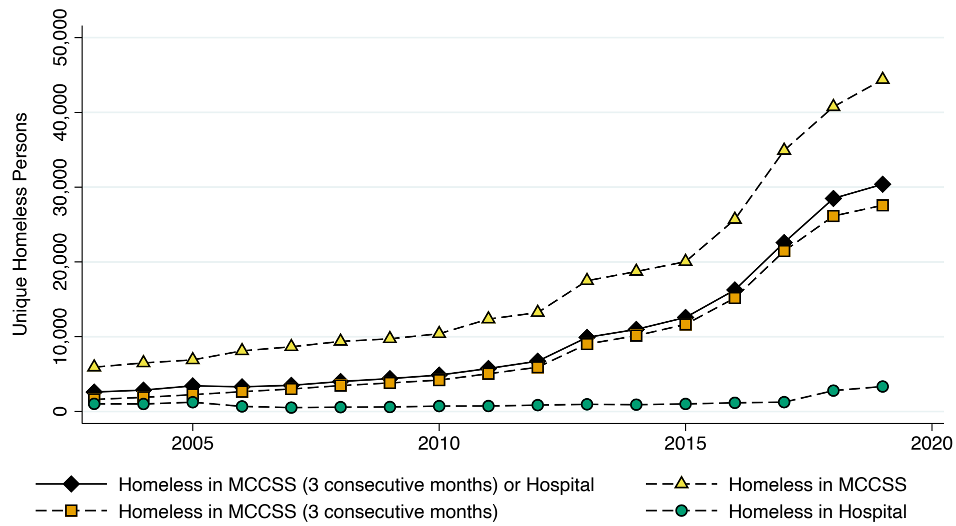
D.1 Data

We draw on four linked sources. First, we access Ontario's caseload records for Ontario Works (OW) and the Ontario Disability Support Program (ODSP), which are equivalent to British Columbia's Income Assistance and Disability Assistance programs, respectively. These files record an accommodation type for each recipient-month; we define homelessness as an accommodation type of Emergency Hostel, Homeless, or Transient. Second, the Discharge Abstract Database (DAD) records inpatient hospitalizations and flags a homelessness-related diagnosis. Third, the National Ambulatory Care Reporting System (NACRS) records emergency department visits. Fourth, the T1 Family File (T1FF), Statistics Canada's annual tax-based longitudinal file, provides individual- and family-level income measures along with demographic information (age, sex, family composition/marital status) for tax filers up to 2019. All dollar values are adjusted to 2019 dollars using the CPI.

Records are linked at the individual level using an encrypted crosswalk between the MCCSS/health identifier and the tax-file identifier, allowing us to observe both administrative program contact and tax-based income for the same individuals. A limitation of the Ontario data, relative to our main BC analysis, is that we only observe individuals who appear in MCCSS social assistance records at least once in our sample period; we have no information on individuals who are never OW/ODSP recipients.

Figure D.1 shows the counts of unique individuals recorded as homeless in Ontario in each year from 2003 to 2019, using these administrative measures and their union. The number of individuals flagged as homeless in OW/ODSP data for at least one month rises from roughly 6,000 in 2003 to over 44,000 in 2019, with the sharpest increase beginning around 2013 before accelerating after 2015. The number with 3 or more consecutive months of homelessness (following the BC NFA3 definition) rises from roughly 1,600 in 2003 to over 27,500 in 2019. The number identified through a homelessness-related hospital diagnosis is an order of magnitude smaller throughout the period, though it rises in 2018 when Ontario's hospitals began tracking homelessness more diligently. The combined measure, which we use to define homelessness entry throughout this appendix, closely tracks the social-assistance-based series, since the large majority of individuals identified as homeless are captured through social assistance records rather than through a hospital diagnosis alone. We note that the number of OW/ODSP recipients flagged as homeless is about three-quarters of the count reported by Donaldson, Kandyba, and Wang (2026), who estimate the number of individuals who used municipal homelessness services in each year.[29]

Figure D.1: Evolution of the Homeless Population, Ontario



Note: This figure shows annual trends in the number of individuals experiencing homelessness in Ontario at some point during each year, using Ontario administrative records. "Homeless in MCCSS" counts Ontario Works and ODSP (Ontario Disability Support Program) recipients who report their accommodation type as Emergency Hostel, Homeless, or Transient for at least one month in Ontario social assistance (MCCSS) records. "Homeless in MCCSS (3 consecutive months)" restricts this to individuals with this accommodation type for three or more consecutive months. "Homeless in Hospital" counts individuals with a homelessness-related diagnosis code in hospital inpatient discharge records. "Homeless in MCCSS or Hospital" is the union of the hospital homelessness flag and the three-consecutive-month MCCSS measure.

D.2 Event Studies Around Homelessness Entry

We define homelessness entry as the earlier of (i) the first month of a three-or-more consecutive month spell with an Emergency Hostel, Homeless, or Transient accommodation type in MCCSS data, or (ii) the first hospitalization with a homelessness diagnosis. For the health and social assistance receipt analysis, the sample includes individuals whose first entry occurred between 2008 and 2016 and who were aged 19–60 at entry, observed monthly from 48 months before to 36 months after entry. For the tax-based event studies, we further restrict entry years to 2008–2014, since the T1FF panel ends in 2019 and we require up to five years of post-entry data; the sample is restricted to individuals aged 19–60 at entry and

[29]The authors access municipally-kept files on service users, but these files vary in accuracy. The authors make various imputations.

in each observed year. We construct an annual panel around entry. Income measures are only observed for individuals who filed a T1 tax return in that year.

Figure D.2 reports event studies for health-care contact and benefit receipt around homelessness entry. Panel (a) plots the likelihood of an ER visit in a month, which rises from 7% four years prior to onset to 14% in the month before entry. Panel (b) shows a similar pattern for the average number of ER visits, which rises from 0.11 four years prior to onset to 0.29 the month before entry. Panels (c) and (d) show that inpatient visits only increase in the months just prior to homelessness entry. The share with at least one inpatient visit remains low and roughly flat until shortly before onset, rising from under 1% four years prior to 2% the month before entry. The average number of hospital inpatient visits follows the same pattern. These patterns closely match those in Figures 6 and E.11 from our BC data.

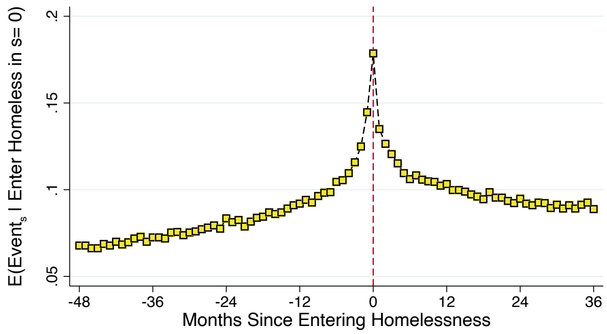
Panels (e) and (f) display trends in Ontario's equivalent to Income Assistance and Disability Assistance (Ontario Works and ODSP), mirroring the gradual pre-entry rise documented for IA/DA receipt in our main BC analysis (Figure 5, panel c). The share receiving income assistance rises from 24% four years before onset to 35% in the month before entry. The share receiving income assistance or disability assistance follows the same gradual pre-entry rise, from 38% to 52%. As in our main BC analysis, this slower, more gradual rise in benefit receipt contrasts with the sharper acceleration in health-care contact immediately before onset.

Figure D.3 reports event studies for tax-based income and employment measures. Panel (a) shows that the share of the sample with a matched T1 tax record is fairly stable between 54% and 59%. Panels (b) through (d) show consistent patterns of economic deterioration leading up to entry: the share with positive employment earnings falls from 51% six years before onset to 38% in the year before entry, employment earnings themselves fall from $9,400 to $4,800 over the same period, and total individual income falls from $16,200 to $13,200. All three then fall more sharply in the year of entry.

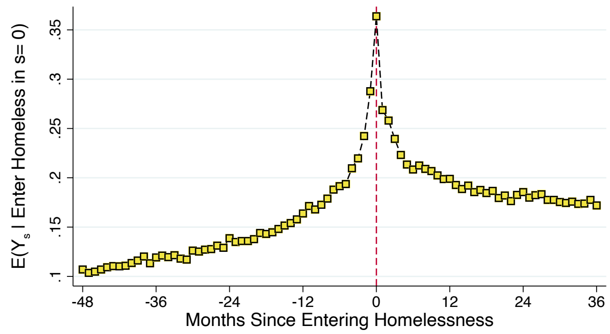
Together, these two figures complement our main BC-based analysis in two distinct ways. First, Figure D.2 provides an external validity check: in a different province and time period, but with similar administrative measures of homelessness, we observe similar pre-entry deterioration in health care contact and benefit receipt. This suggests that our main findings are not an artifact of BC-specific program rules, the particular administrative systems that produce our data, or the specific years we study. Second, Figure D.3 allows us to study income measures we do not observe in our BC data. While our BC analysis proxies economic circumstances using IA and DA receipt, the Ontario tax-based figure shows that this proxied deterioration is mirrored in actual income and is driven primarily by a decline in employment earnings, partly offset by government transfers.

Figure D.2: Event Studies: Health and IA/DA – Ontario

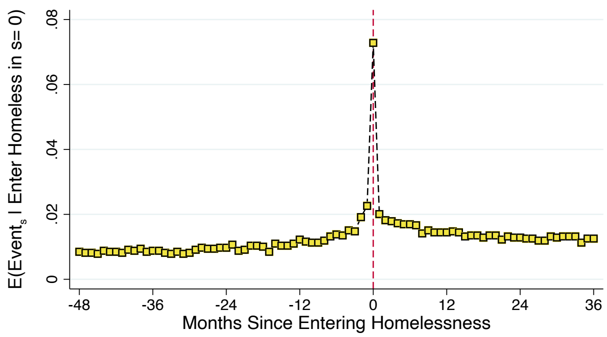
(a) Visited ER



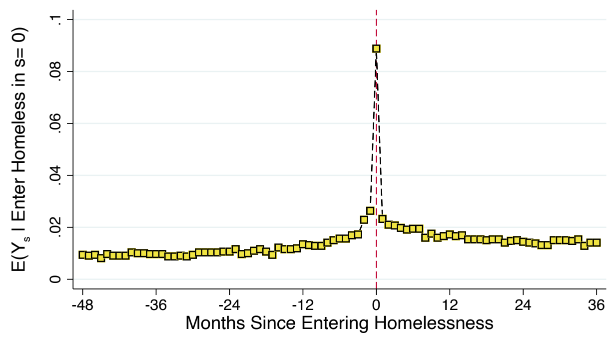
(b) Number of ER Visits



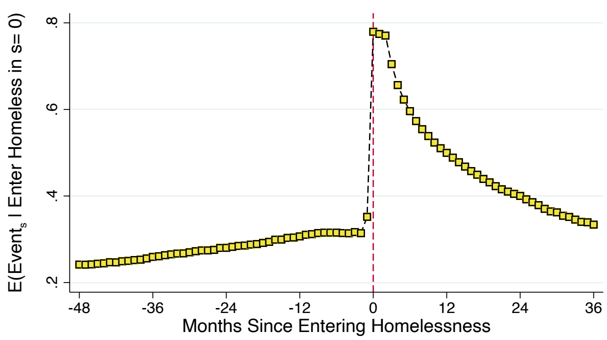
(c) Visited Inpatient



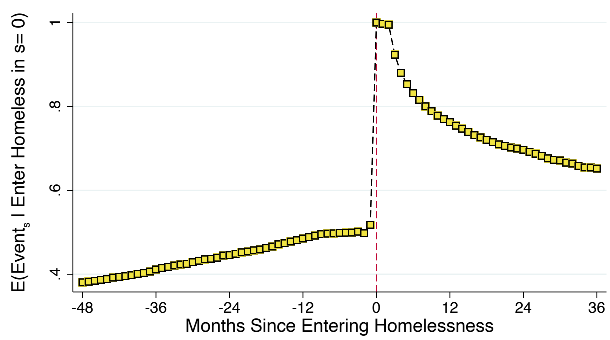
(d) Number of Inpatient Visits



(e) Received IA

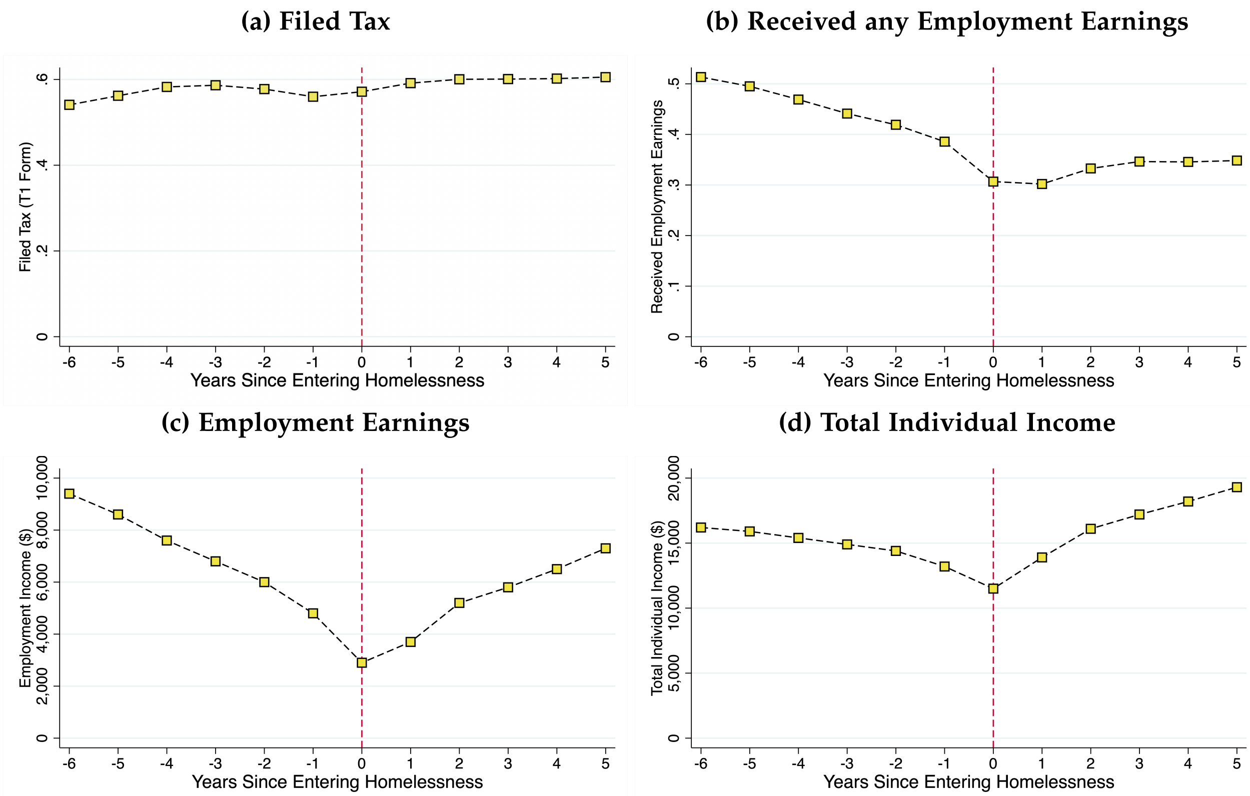


(f) Received IA or DA



Note: This figure replicates the main event-study analysis using an independent administrative data source from Ontario (MCCSS). The sample consists of individuals whose first observed homelessness spell occurred between 2008 and 2016 and who were aged 19–60 at entry. Homelessness entry is identified as the earlier of two flags: three consecutive months with an accommodation type of Emergency Hostel, Homeless, or Transient recorded in Ontario welfare records, or a homelessness-related diagnosis code in hospital records. ER visits are drawn from the National Ambulatory Care Reporting System (NACRS) and hospital visits from the Discharge Abstract Database (DAD). Panels (a) and (c) show the share of individuals with at least one ER visit and one hospital visit, respectively, in each month relative to homelessness entry; panels (b) and (d) show the corresponding average number of visits. Panels (e) and (f) show the share of individuals receiving income assistance (IA, i.e., Ontario Works) and the share receiving IA or disability assistance (DA, i.e., the Ontario Disability Support Program), respectively. The horizontal axis denotes months since first entering homelessness, from 48 months prior to 36 months after.

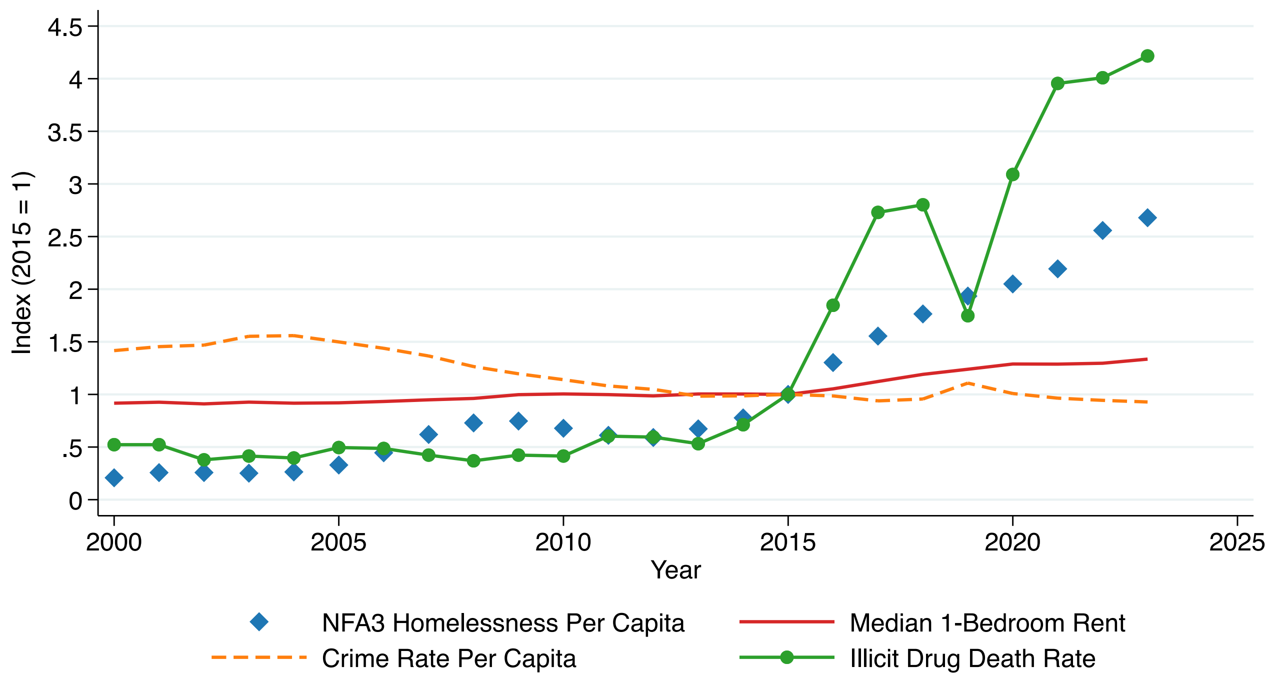
Figure D.3: Event Studies: Income and Employment – Ontario



Note: This figure presents event-study trajectories of tax-based income and employment measures around homelessness entry, using tax files (T1FF) linked to Ontario social assistance and hospital records. The sample includes individuals whose first observed homelessness spell occurred between 2008 and 2014, restricted to those aged 19–60 at entry and in each observed year. The horizontal axis denotes years since first entering homelessness. Panel (a) shows the share of the sample with a matched T1 tax record in each event year. Panels (b)–(d) are conditional on having filed a T1 form; panel (b) shows the share with positive employment earnings (greater than $500); panel (c) shows average employment earnings; and panel (d) shows average total individual income. All dollar amounts are in 2019 Canadian dollars.

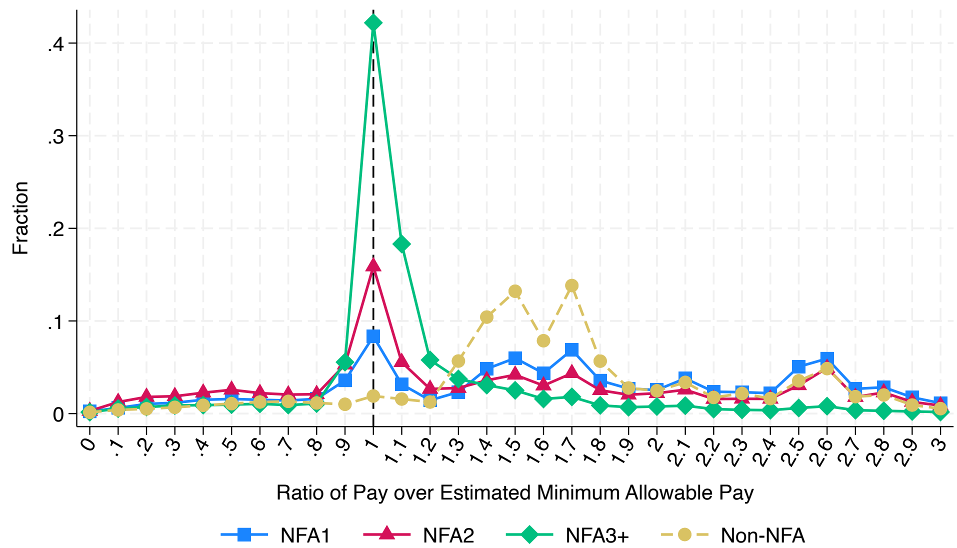
E. Supplemental Results

Figure E.1: Homelessness, Rent, Crime, and Drug Deaths Over Time



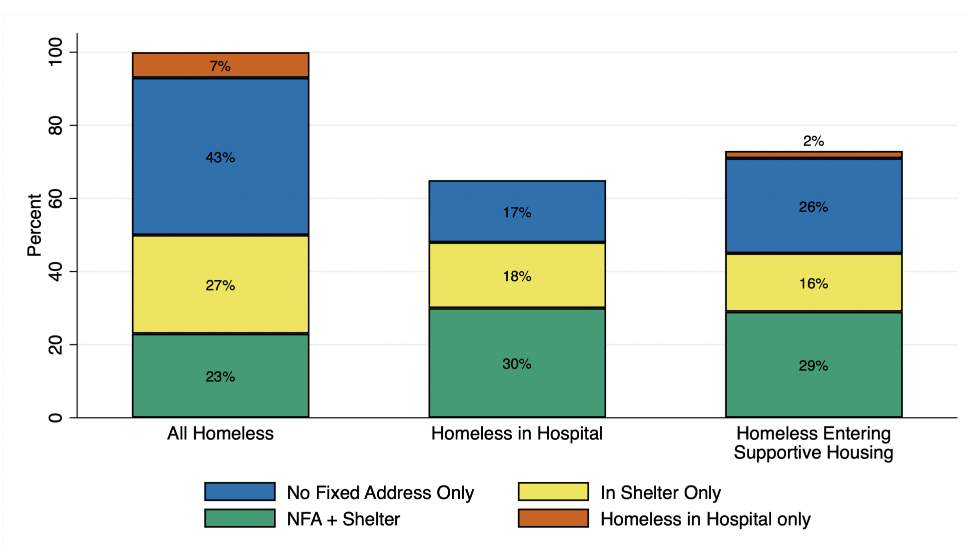
Note: This figure presents the evolution of the homelessness rate along potential aggregate drivers. Homelessness per capita is calculated as the number of unique individuals who were flagged as having No Fixed Address in the IA/DA for 3 consecutive months, divided by the population that year. All series are indexed to 1 in 2015.
Source: Statistics Canada. Table 35-10-0184-01 Incident-based crime statistics, by detailed violations, police services in British Columbia – not from BC Data Innovation Program Data;
Canada Mortgage and Housing Corporation Rental Market Survey;
Drug Toxicity Deaths: British Columbia Vital Statistics.

Figure E.2: Ratio of Social Assistance Received Over Minimum Allowable Amount, by NFA Status



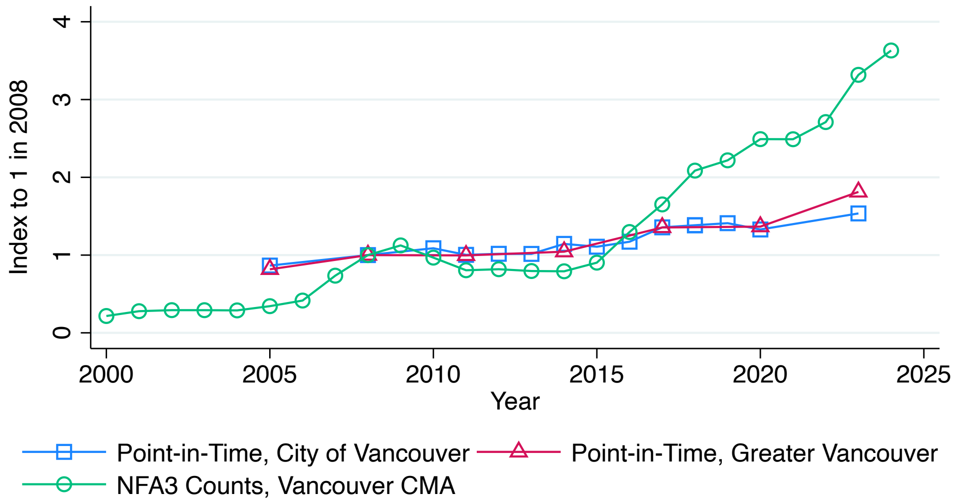
Note: The fraction of all person-months of IA/DA receipt where the ratio of dollars received to the minimum allowable amount was within a certain range (e.g., 0.95-1.05, plotted at ratio = 1). The estimated minimum allowable amount is equivalent to receiving only the basic amount plus the minimum monthly shelter allowance, typically implying the recipient did not report meaningful shelter expenses. The solid lines represent individuals in an NFA spell of exactly one month, exactly two months, and three months or more, respectively. The dashed line represents recipients who report having a fixed address.

Figure E.3: Decomposition of Homeless Population by Measure and Validation Checks



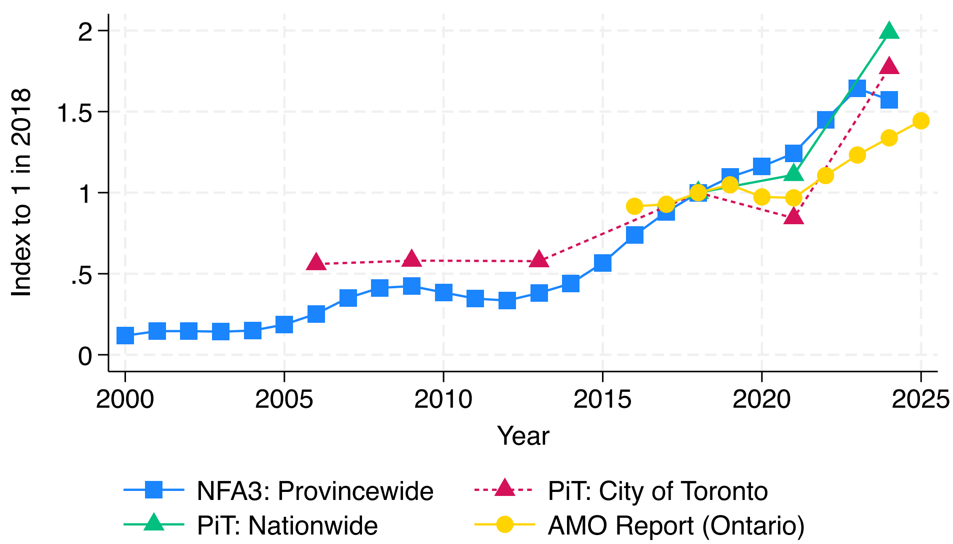
Note: The first bar decomposes the stock of "any homeless" into the proportions accounted for by different homelessness measures: NFA only, NFA and shelter in the same year, shelter only in the year, and persons flagged as homeless in hospital but not NFA or shelter. The second bar shows the fraction of the homeless in the hospital population who were homeless according to NFA or shelter in the same year. The third shows, among the supportive housing entrants who reported being homeless before entry, what fraction we flag as homeless using the other measures during the same year.

Figure E.4: Trends in Homelessness Measured by Point-in-Time Street Counts



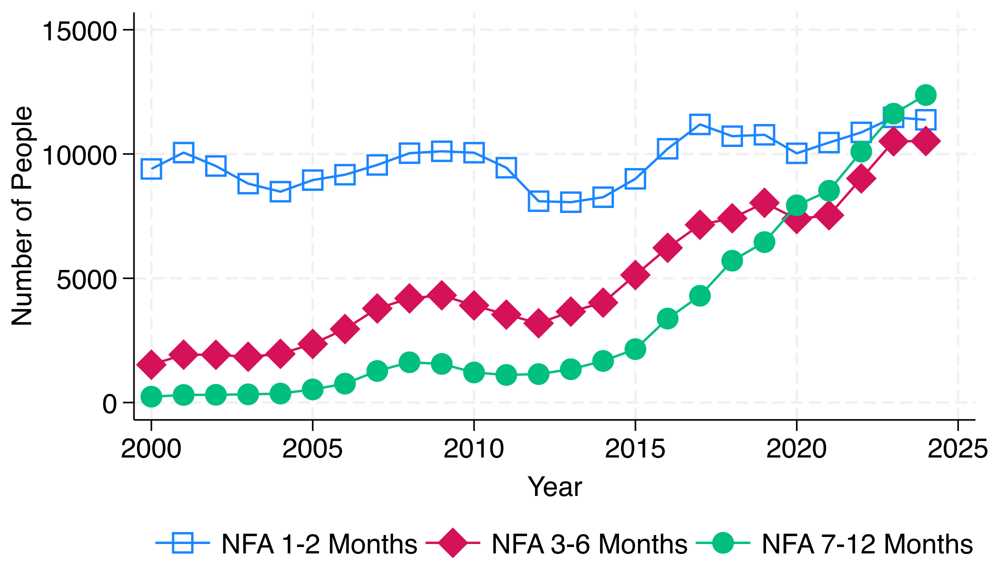
Note: Trends in the number of people recorded as homeless according to our NFA3 measure for the Vancouver Census Metropolitan Area and the Point-in-Time Street and Shelter Homeless Counts conducted once per year, for the city of Vancouver and Greater Vancouver, respectively. The latter includes neighbouring cities in addition to Vancouver (e.g. Richmond, Burnaby and others). The three series are indexed to 1 in 2008.

Figure E.5: Trends in Homelessness Across Data Sources and Geographies



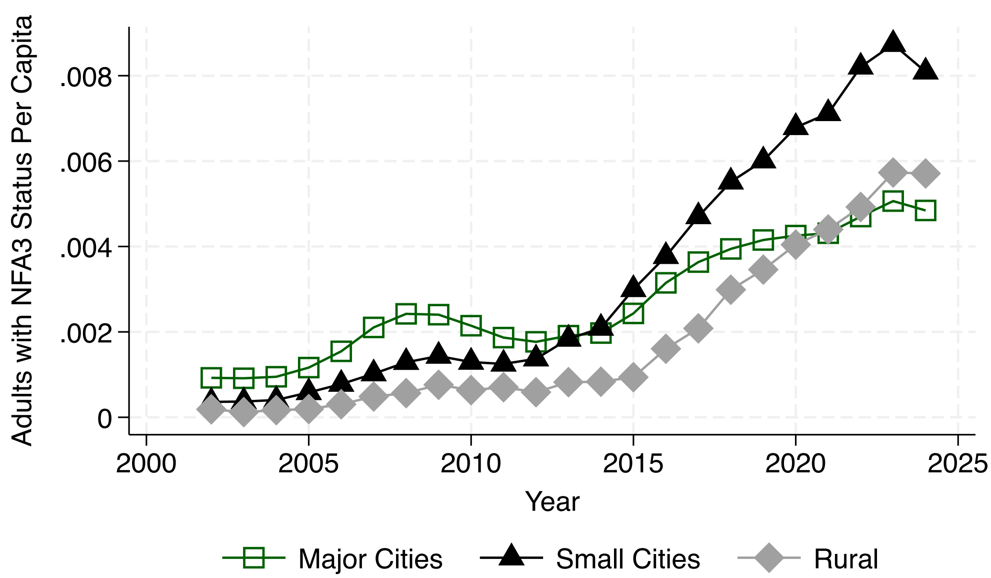
Note: This figure compares BC NFA3 trends to nationwide and Toronto point-in-time (PiT) counts, and Ontario-wide homelessness estimates from the Association of Municipalities of Ontario (AMO). Each series is indexed to 1 in 2018, the first year in which nationwide PiT estimates are available. *Sources:* Toronto PiT: City of Toronto. Street Needs Assessment Results Report, 2024 and 2021. National PiT: Housing, Infrastructure and Communities Canada. Everyone Counts 2024, Highlights Report Part 1 – Enumeration of Homelessness. AMO Report: Municipalities Under Pressure: The Human and Financial Cost of Ontario's Homelessness Crisis; Municipalities Under Pressure One Year Later: An Update on the Human and Financial Cost of Ontario's Homelessness Crisis.

Figure E.6: NFA Flagged Persons, by # of NFA Months Received During the Year



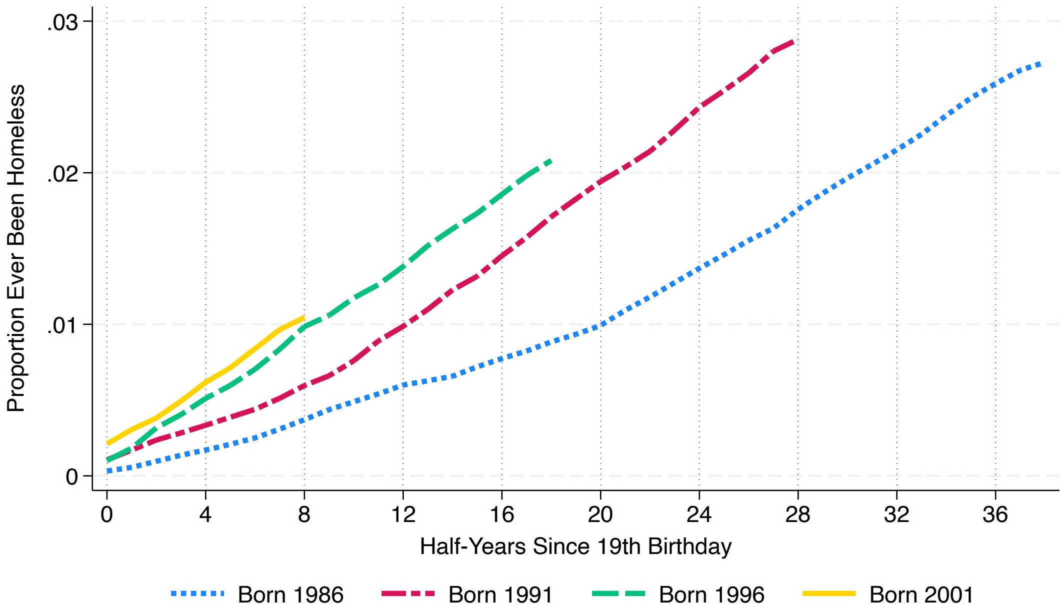
Note: This figure shows the number of unique individuals (of any age) that had no fixed address at any point in a given year, split by the number of NFA months they had within that calendar year.

Figure E.7: Trends in "NFA3" Homelessness Per Capita (Adults Only), by Region



Note: The per-capita rate of NFA3 homelessness among 19-64 year-olds, in each year from 2002-2024, for different geographies. These geographies include: (i) Major cities (BC's 7 Census Metropolitan Areas); (ii) Small cities (the province's Census Agglomerations); and (iii) all rural areas (those not designated as a CMA or CA) combined. An individual is counted as homeless in a given year if they have NFA3 status at any point in that year.

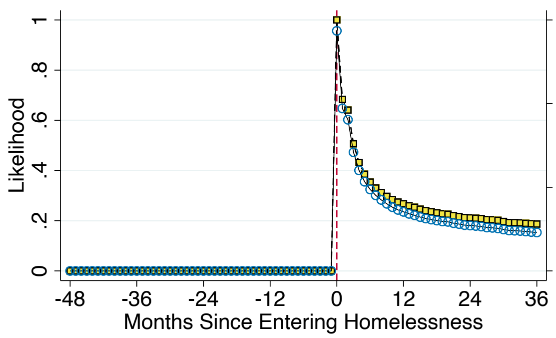
Figure E.8: Cumulative Probability of Homelessness (NFA3).



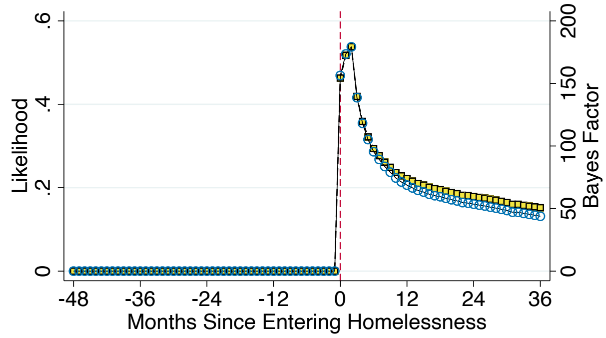
Note: This figure plots the cumulative probability of entering an NFA3 spell for the first time, at six-month intervals beginning in the month an individual turns 19. Each line represents individuals born in 1986, 1991, 1996, and 2001, respectively. The sample includes people who were raised in BC, and continuously present in the province from age 19 to December 2023, or their first month experiencing homelessness (whichever comes first). For further details on sample construction, see Appendix A.3.2.

Figure E.9: Event Studies: Homelessness and Housing Measures

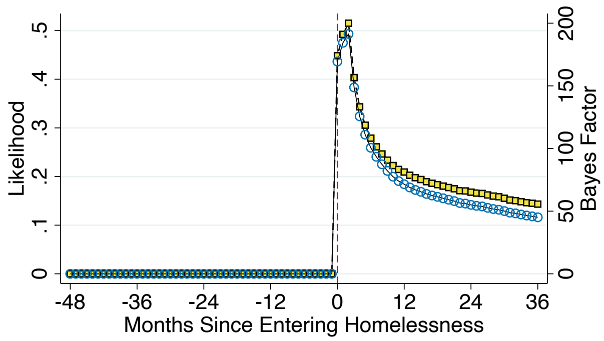
(a) Any Homeless



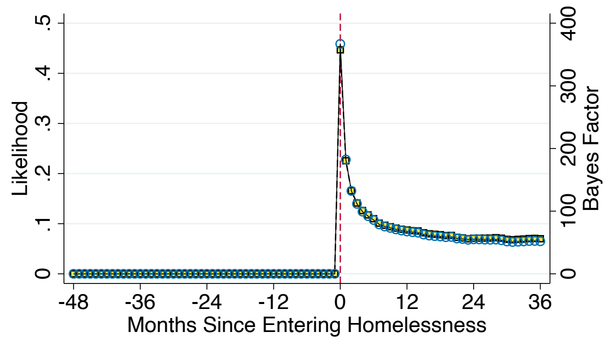
(b) Any NFA Status



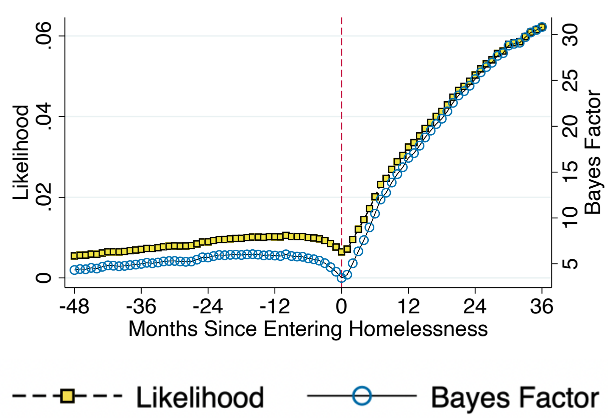
(c) NFA3



(d) In Shelter

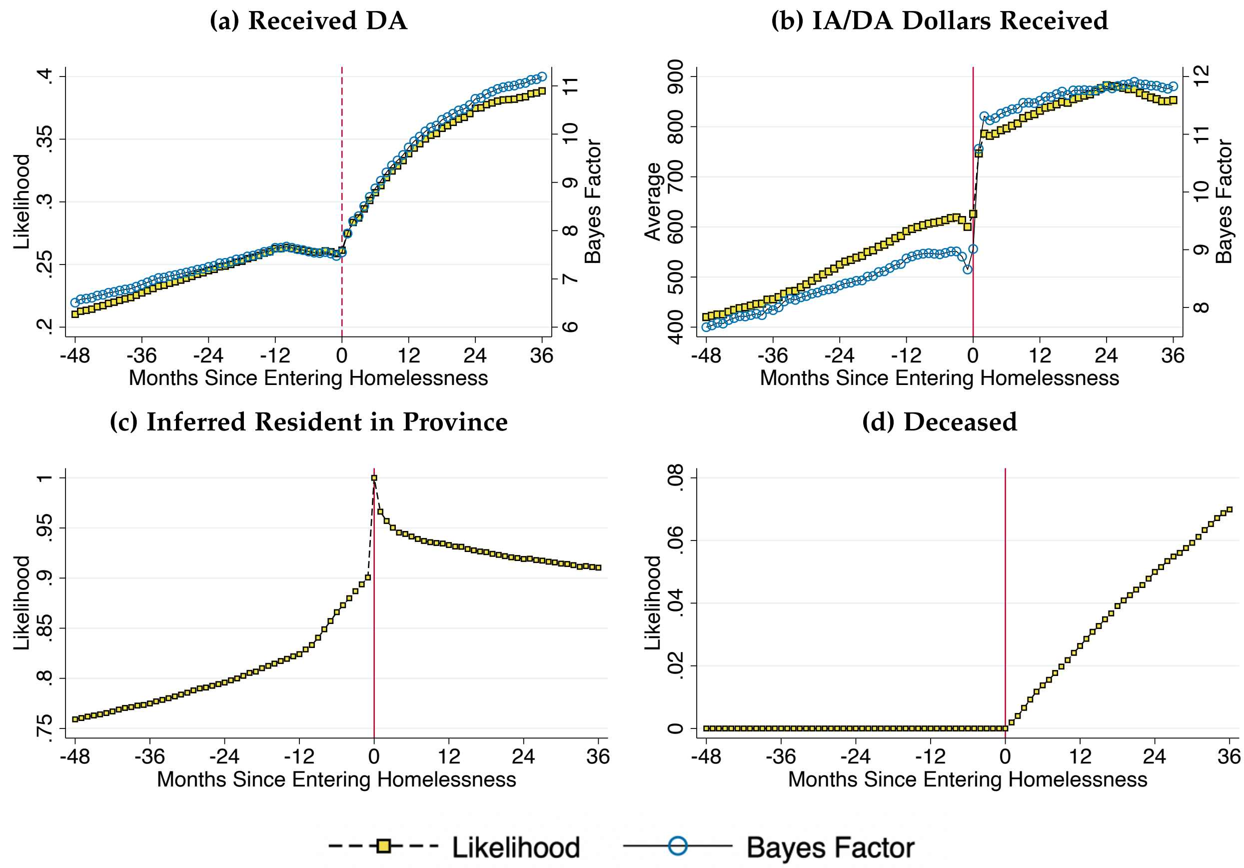


(e) In Supportive Housing



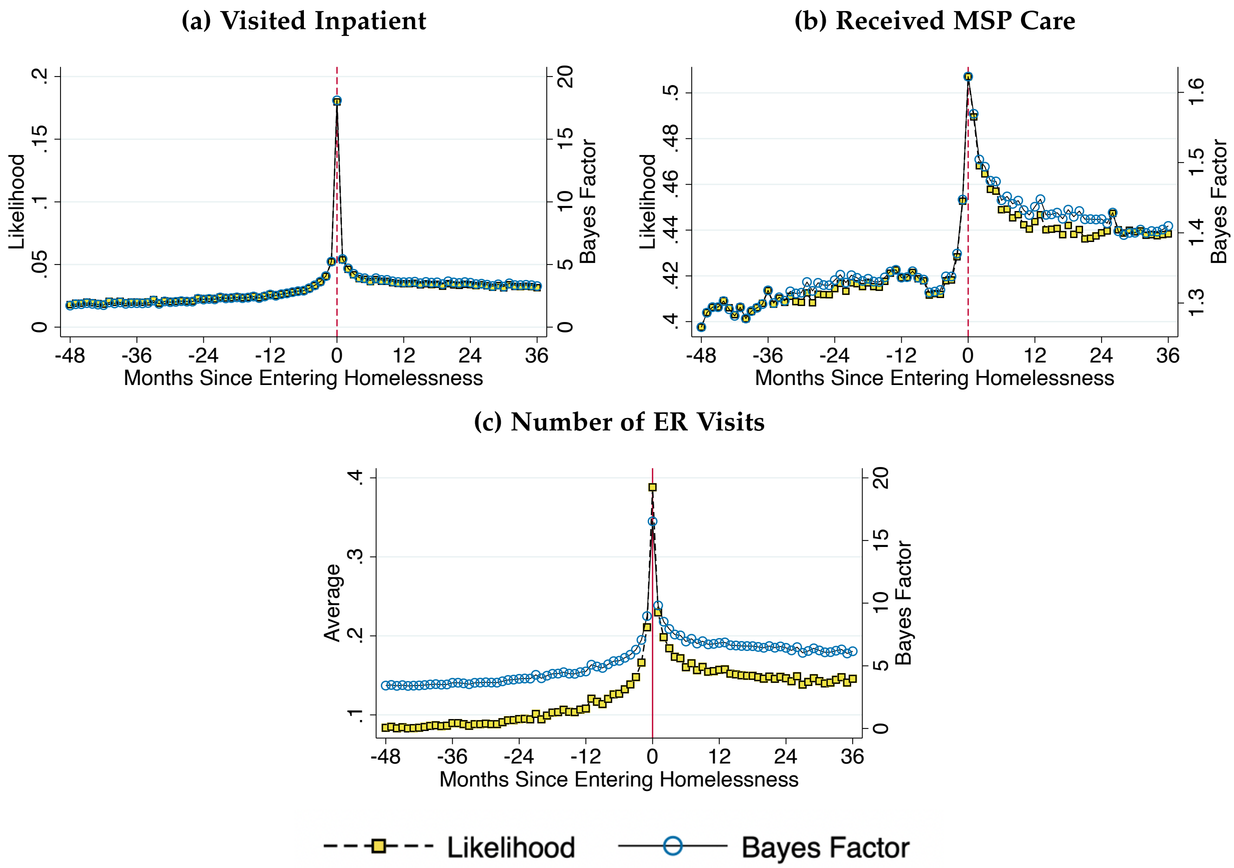
Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that the outcome among homeless entrants is 15 times larger than that among non-entrants in event month s.

Figure E.10: Event Studies: Income Support, Resident Status, and Mortality



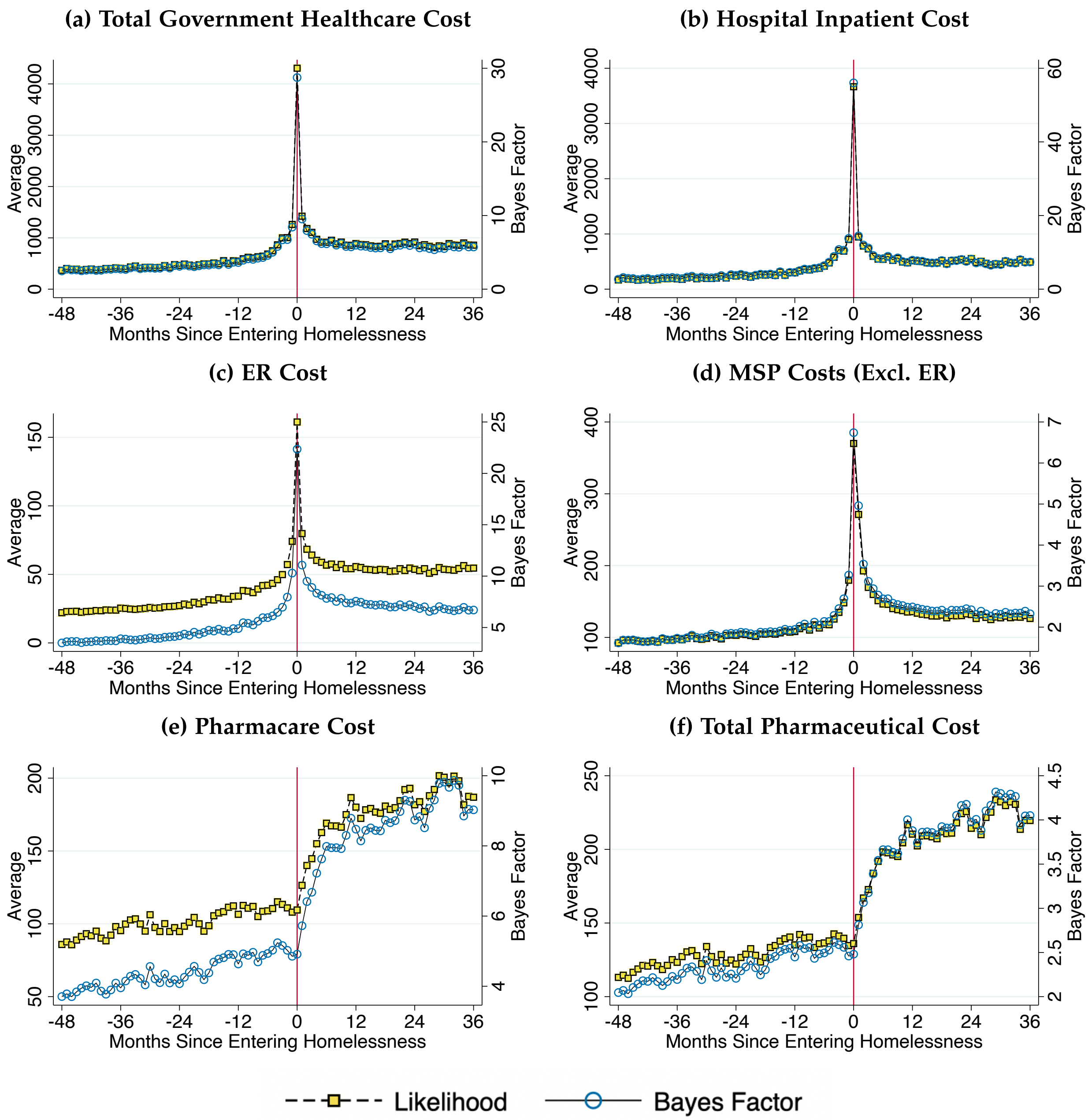
Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that the outcome among homeless entrants is 15 times larger than that among non-entrants in event month s.

Figure E.11: Event Studies: Healthcare Service Use



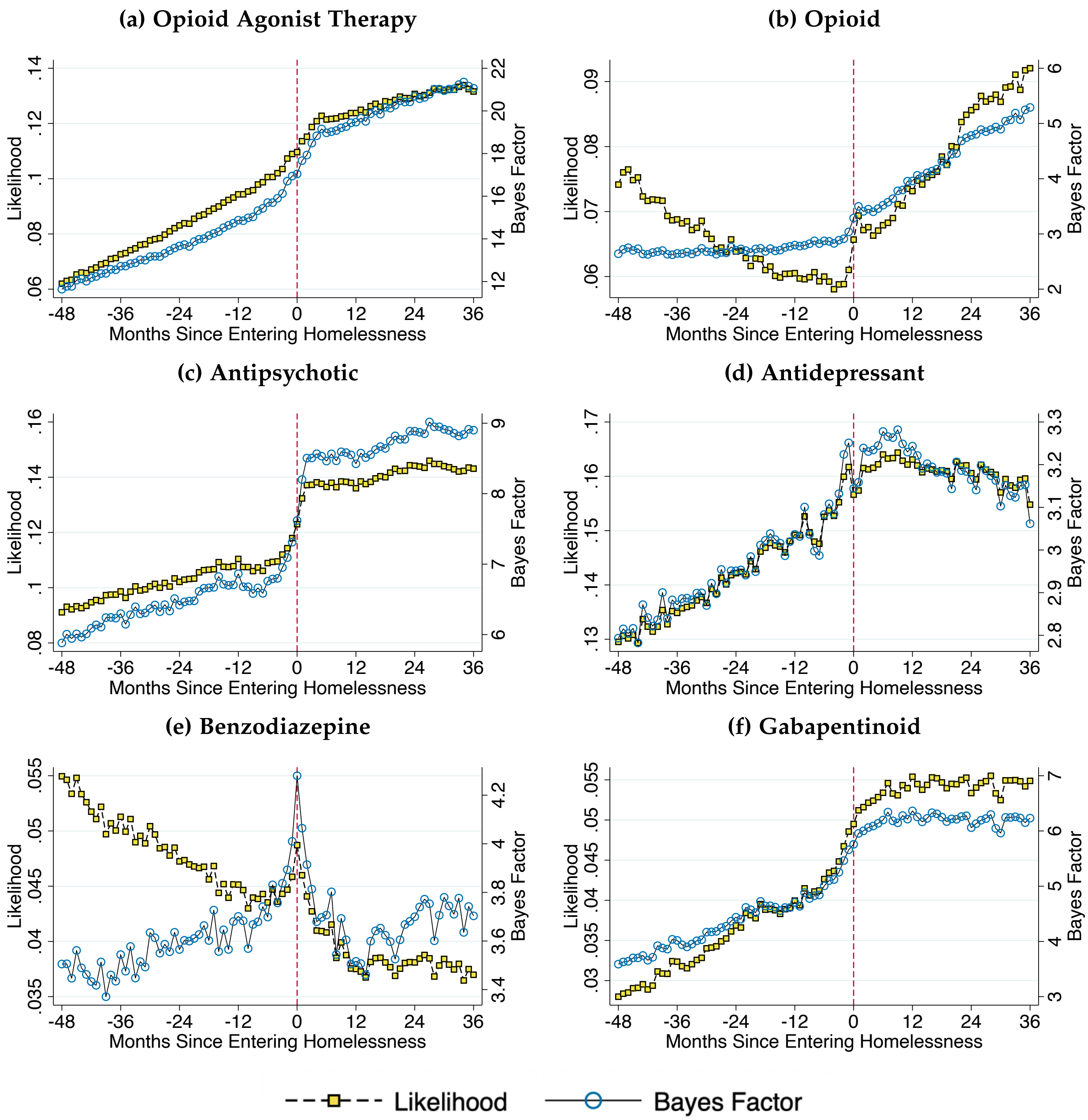
Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that the outcome among homeless entrants is 15 times larger than that among non-entrants in event month s.

Figure E.12: Event Studies: Healthcare Cost Components



Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that the outcome among homeless entrants is 15 times larger than that among non-entrants in event month s.

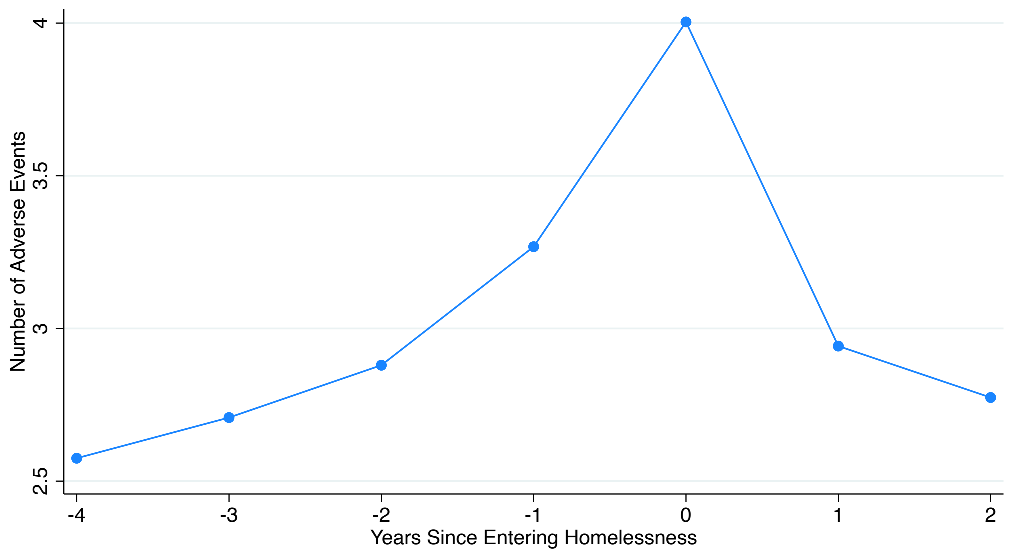
Figure E.13: Event Studies: Prescriptions Received



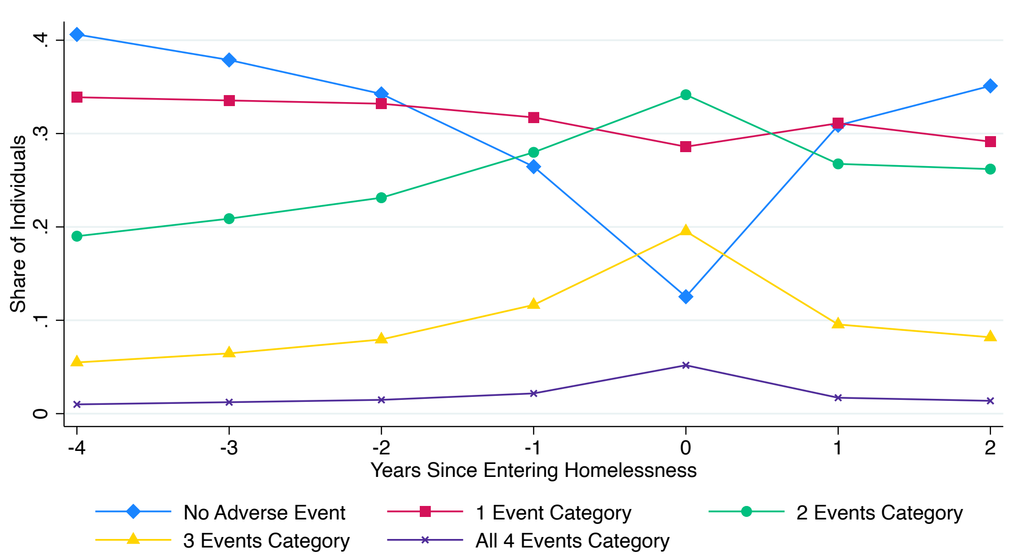
Note: The figure shows event-study plots of outcomes in each month relative to first entry into homelessness. The yellow squares show the average of each outcome in month s among homeless entrants — $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. The blue circles divide this by the corresponding average in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. A Bayes Factor of 15, for example, means that the outcome among homeless entrants is 15 times larger than that among non-entrants in event month s.

Figure E.14: Event Studies: Number of Adverse Events

(a) Average Number of Adverse Events

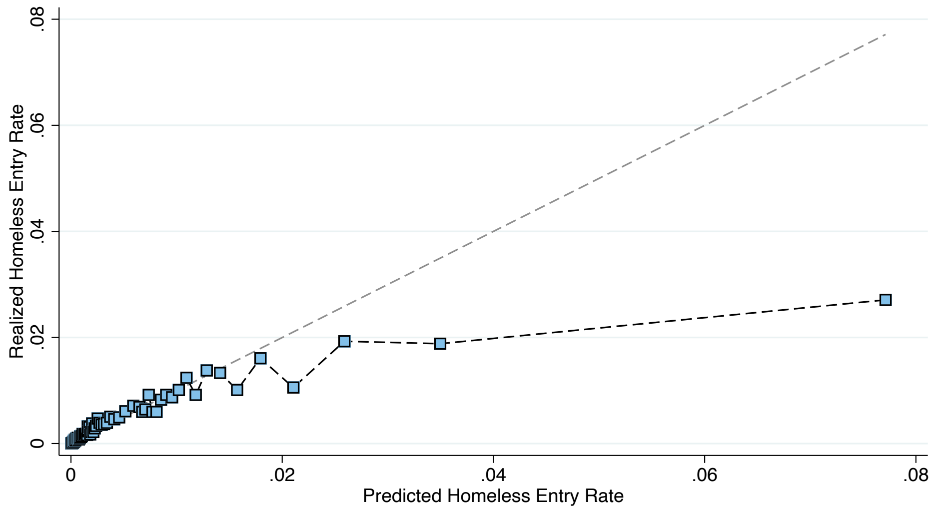


(b) Number of Adverse Events



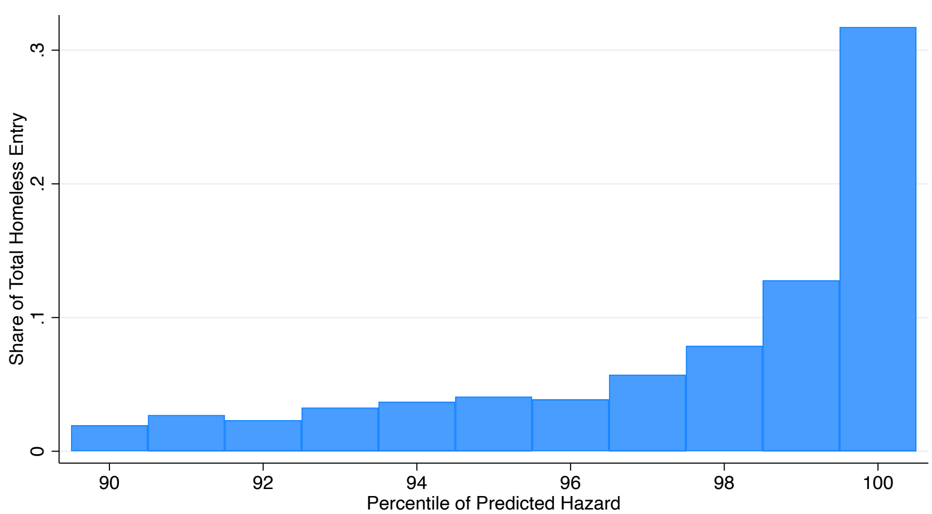
Note: This figure presents the yearly number of adverse events surrounding first-time homelessness entries between 2018 and 2023. We define an adverse event as one of the following: being alleged to have committed a crime or being discharged from custody; ER visit, inpatient visit, or treatment for substance-use-related issues, mental health disorders, or head injury; receipt of alcohol use disorder treatment, antidepressants, antipsychotics, benzodiazepines, gabapentinoids, opioids, or opioid agonist therapy; a new diagnosis of substance use disorder, chronic mental illness, schizophrenia, or other chronic disease; family dissolution; or a new IA/DA spell. Panel (a) plots the average number of adverse events experienced per individual in each year relative to first homeless entry, where time -1 represents the 12 months before entry. Panel (b) plots the share of individuals experiencing events in exactly 0, 1, 2, 3, or all 4 adverse event categories in each year relative to entry. The four categories are: (i) criminal justice events, (ii) substance- or alcohol-related events, (iii) other health events, and (iv) family dissolution or initiation of an IA/DA spell.

Figure E.15: Out of Sample Prediction Results, Baseline Model



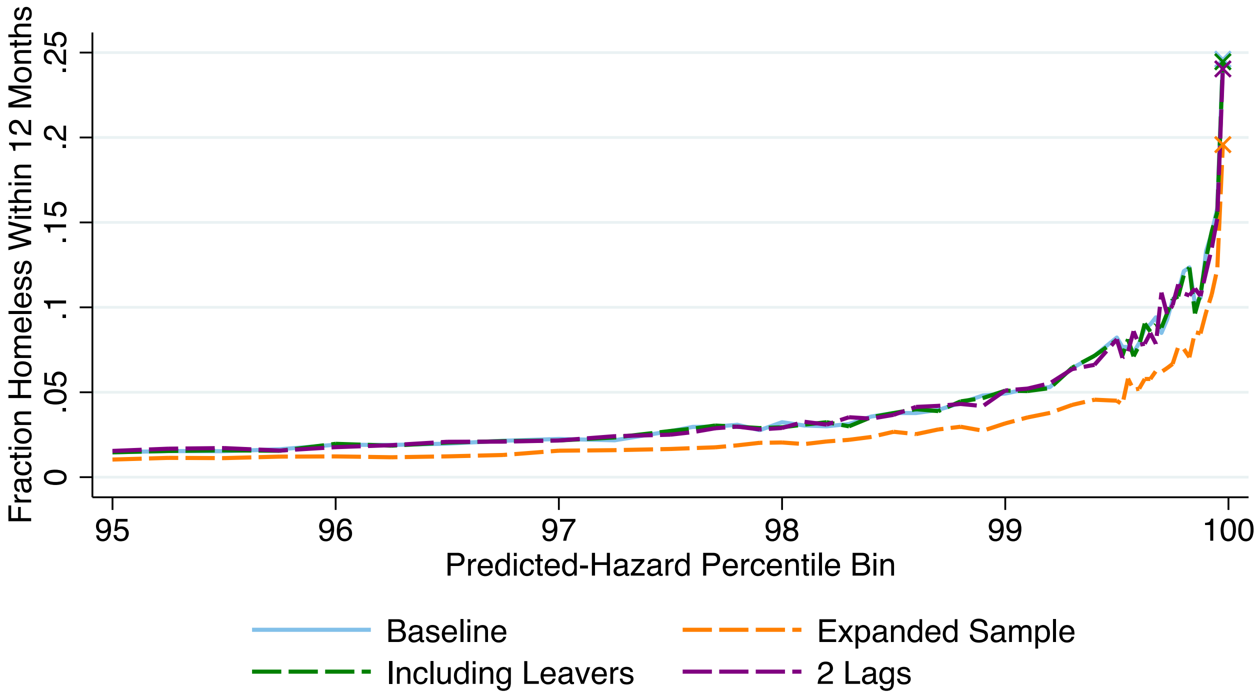
Note: This figure reports out-of-sample prediction results from the Cox proportional hazard model estimated on data through December 2022 and applied to 2023–2024. The sample is restricted to BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. Each observation is a person-month. The horizontal axis represents the predicted entry rate, while the vertical axis shows the realized entry rate in the next month. Each marker is a percentile bin of predicted risk, where the top bin contains 0.025% of the population of interest with the highest predicted hazard ratio. The gray dashed line is a 45° line that represents perfect prediction.

Figure E.16: Share of Realized Entry by Risk Bin



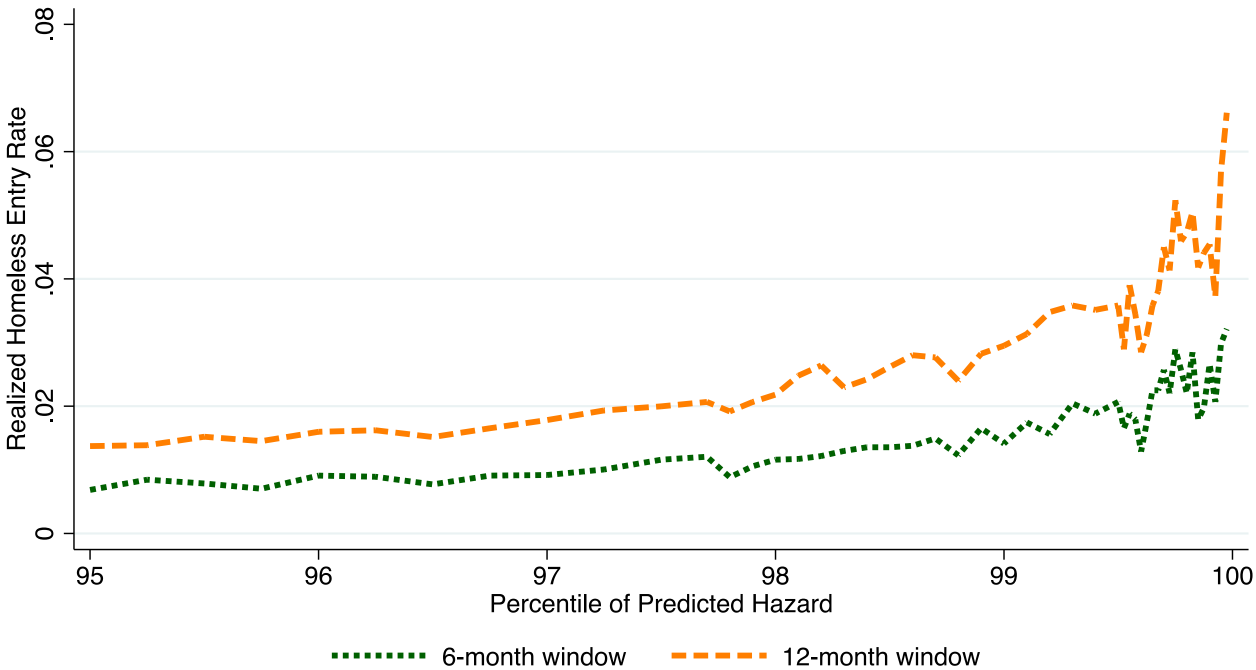
Note: This figure displays out-of-sample recall for the predicted homelessness risk score. For each percentile bin of predicted risk, we plot the share of all first-time homeless entrants in the hold-out period (January–December 2023) with predicted risk in the month of entry falling within that bin. The figure displays only the top decile of the predicted risk distribution to highlight variation where concentration is greatest.

Figure E.17: Out of Sample Prediction, Alternative Sample and Specification



Note: This figure reports out-of-sample prediction results comparing four specifications of the Cox proportional hazard model. The models are estimated on data through December 2022 and applied to 2023–2024. Each observation is a person-month, the horizontal axis is the predicted hazard percentile bin, and the vertical axis is the realized fraction of observations where the individual entered homelessness for the first time within the subsequent 12 months. We only present the 95th–100th percentiles of the predicted risk distribution, since for lower predicted risk groups, the homelessness entry rate is near zero. *Baseline* refers to the main sample: BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. *2 Lags* is a robustness check to address potential measurement error in the timing of entry into homelessness: the probability of entering homelessness is modelled using covariates observed two months prior (rather than one month prior). *Including Leavers* relaxes the baseline restriction that individuals remain in BC throughout the sample period; individuals who leave BC are included in the regression sample up until the month they depart. *Expanded Sample* broadens the sample beyond BC-raised individuals to include anyone present in BC during 2017–2023, regardless of whether they grew up in the province; as a result, all childhood variables are omitted from this specification.

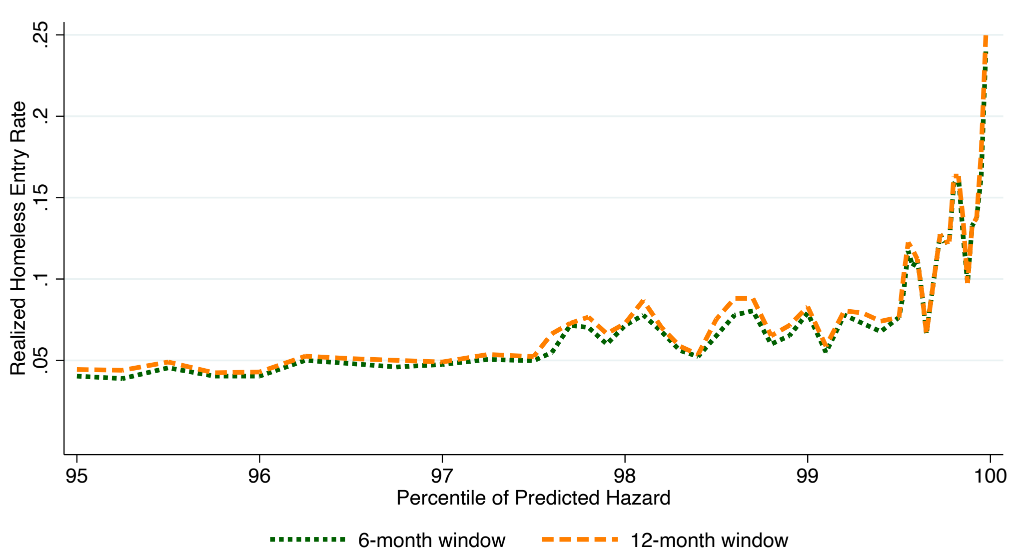
Figure E.18: Out of Sample Prediction, No Contemporaneous Variables



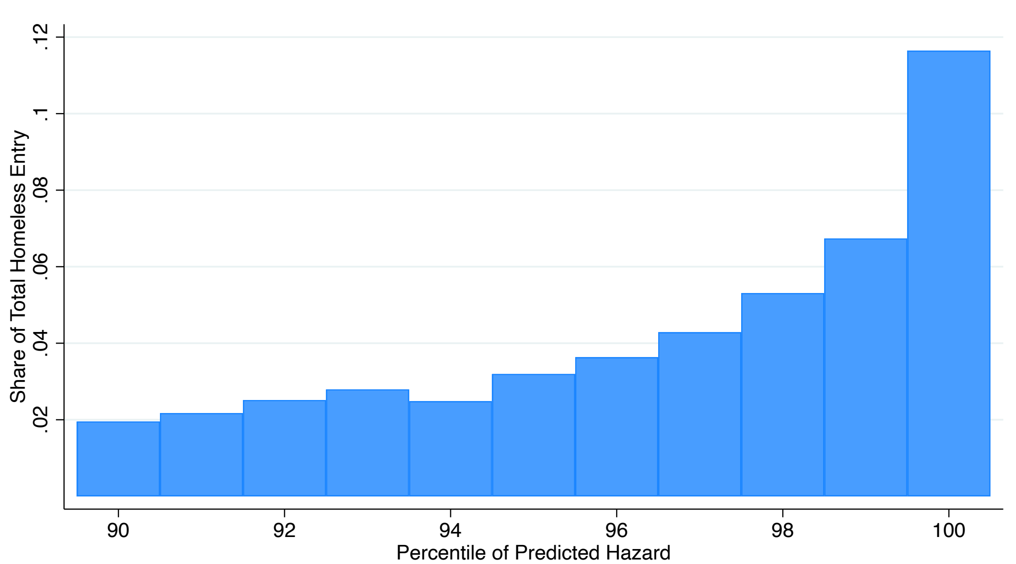
Note: This figure reports out-of-sample performance for a Cox proportional hazard model trained on only childhood variables. The model is estimated on data through December 2022 and applied to 2023–2024. Each observation is a person-month, the horizontal axis is the predicted hazard percentile bin, and the vertical axis is the realized fraction of observations where the individual entered homelessness for the first time within the subsequent 12 months. We only present the 95th–100th percentiles of the predicted risk distribution, since for lower predicted risk groups, the homelessness entry rate is near zero.

Figure E.19: Out of Sample Prediction IA/DA recipients

(a) Realized Entry by Predicted Bins



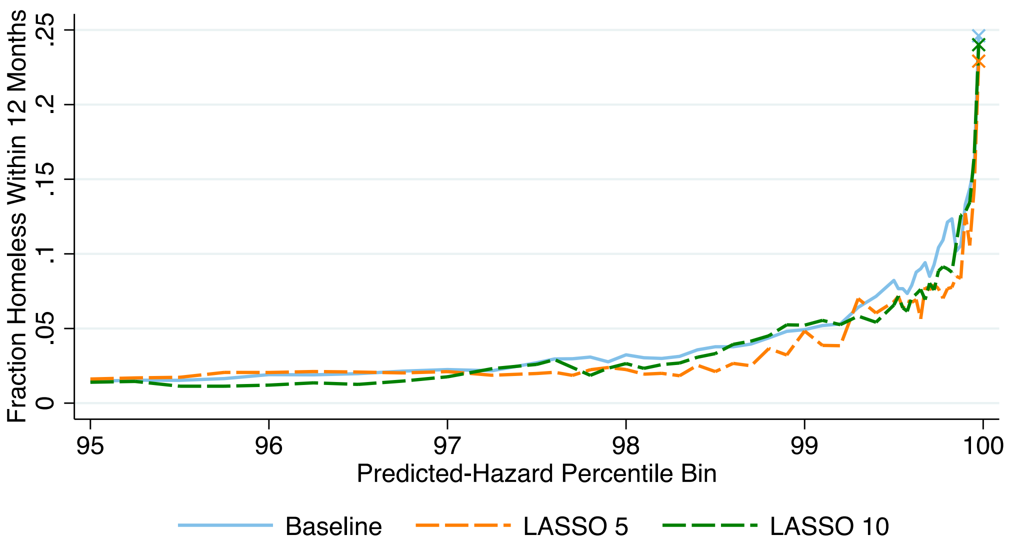
(b) Share of Realized Entry by Risk Bin



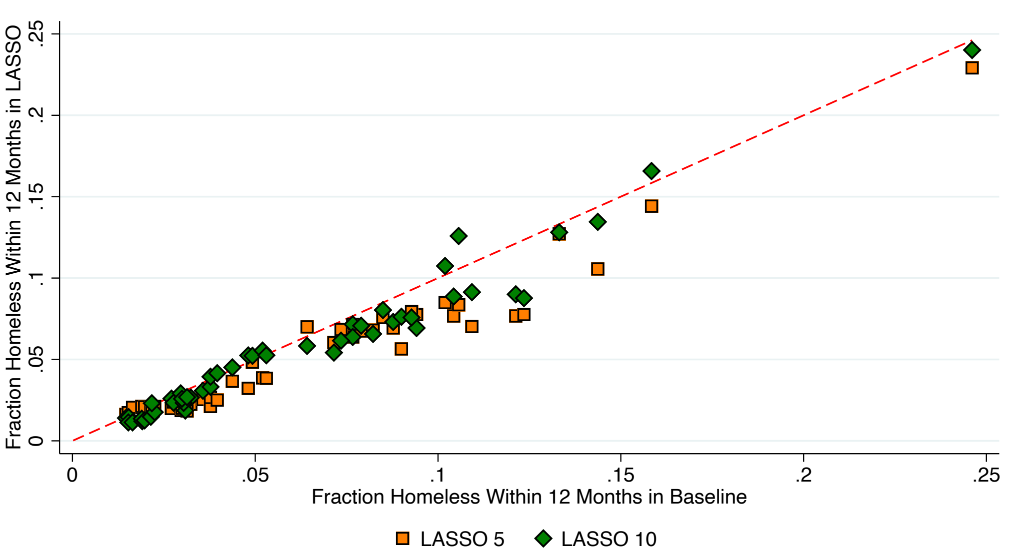
Note: This figure reports out-of-sample performance for a Cox proportional hazard model trained on IA/DA recipients only (see Appendix C for a full sample description). The model is estimated on data through December 2022 and applied to 2023–2024. Each observation is a person-month. In both panels, the horizontal axis is the predicted hazard percentile bin. In Panel (a), the vertical axis is the realized homelessness entry rate over the subsequent 6- or 12-month period. In Panel (b), each bar represents the share of all first-time homeless entrants in 2023, with predicted risk in the month of entry falling in a given bin.

Figure E.20: Out of Sample Prediction LASSO

(a) Realized Entry by Predicted Bins



(b) Realized Entry by Baseline Bins



Note: This figure reports out-of-sample prediction results comparing the baseline Cox proportional hazard model to two models where LASSO selected the 5 and 10 most important covariates, respectively. The models are estimated on data through December 2022 and applied to 2023–2024. The sample is restricted to BC-raised individuals born in 1986 or later who were continuously present in the province through the test period and had not yet experienced homelessness. Each observation is a person-month. In Panel (a), the horizontal axis is the predicted hazard percentile bin. The vertical axis is the realized first-time homeless entry rate within the next 12 months. In Panel (b), each point corresponds to a particular predicted-hazard percentile bin. The horizontal axis is the realized homeless entry rate over the next 12 months, where the bin is assigned using the baseline model. The vertical axis is the realized homeless entry rate over the next 12 months, for bins assigned using the 5-covariate or 10-covariate models. We only present the 95th–100th percentiles of the predicted risk distribution, since for lower predicted risk groups, the homelessness entry rate is near zero.

Table E.1: Descriptive Statistics by Homelessness Status

Variable	Housed	On IA/DA, Housed	Any Homeless	Long Homeless	Short Homeless	NFA 1–2 Mo.	NFA3	NFA3, No Shelter	In Shelter	Homeless Hospital
Panel A: Homelessness Measures										
Linkable identifier	1.000	0.998	0.936	0.991	0.907	0.992	0.994	0.991	0.887	1.000
Any homeless measure	0.000	0.000	1.000	1.000	1.000	0.217	1.000	1.000	1.000	1.000
NFA3 or shelter	0.000	0.000	0.935	1.000	0.899	0.184	1.000	1.000	1.000	0.653
NFA $\geq$ 3 months (NFA3)	0.000	0.000	0.664	0.920	0.519	0.000	1.000	1.000	0.464	0.477
NFA 1-2 months	0.002	0.033	0.059	0.014	0.084	1.000	0.000	0.000	0.098	0.095
Short homelessness spell (<7 months/year)	0.000	0.000	0.638	0.000	1.000	0.199	0.499	0.580	0.641	0.657
Long homelessness spell ($\geq$7 months/year)	0.000	0.000	0.362	1.000	0.000	0.018	0.501	0.420	0.359	0.343
In shelter	0.000	0.000	0.506	0.502	0.509	0.184	0.354	0.000	1.000	0.479
Homeless in hospital	0.000	0.000	0.186	0.176	0.192	0.066	0.134	0.076	0.176	1.000
Months with NFA3 status	0.00	0.00	4.34	8.96	1.72	0.00	6.53	6.29	3.24	3.41
Months in shelter	0.00	0.00	1.76	2.97	1.07	0.53	1.51	0.00	3.48	1.95
Months homeless in hospital	0.00	0.00	0.26	0.29	0.24	0.09	0.21	0.11	0.27	1.39
Panel B: Income Support										
Received IA or DA	0.050	1.000	0.878	0.969	0.827	1.000	1.000	1.000	0.801	0.843
Received DA	0.034	0.689	0.448	0.522	0.406	0.505	0.488	0.475	0.421	0.556
Months on IA or DA	0.52	10.54	8.74	10.90	7.52	9.40	9.98	9.83	8.10	8.56
Months on DA	0.38	7.67	4.66	5.73	4.05	5.12	5.07	4.93	4.41	5.63
IA/DA dollars received ($)	766	15,406	9,989	11,008	9,410	12,771	10,794	10,786	9,438	10,292
Panel C: Demographics										
Age	41.455	42.703	40.739	41.155	40.503	40.013	40.098	39.770	41.269	41.775
Male	0.497	0.500	0.669	0.699	0.652	0.575	0.659	0.624	0.706	0.703
Household type: Single and childless	0.459	0.747	0.851	0.906	0.819	0.814	0.879	0.851	0.849	0.900
Childless couple	0.214	0.051	0.025	0.019	0.029	0.034	0.024	0.027	0.022	0.024
Household type: Parent in a couple	0.272	0.065	0.022	0.012	0.027	0.036	0.021	0.027	0.016	0.017
Household type: Single parent	0.055	0.137	0.070	0.054	0.078	0.117	0.076	0.094	0.051	0.048
Missing family type	0.001	0.000	0.033	0.009	0.047	0.000	0.000	0.000	0.062	0.010
Born in BC	0.185	0.245	0.250	0.254	0.248	0.276	0.271	0.289	0.220	0.247
Parents unmarried at birth	0.255	0.485	0.649	0.669	0.638	0.609	0.654	0.647	0.663	0.622
Birth weight (standardized)	0.016	-0.149	-0.102	-0.121	-0.091	-0.098	-0.109	-0.099	-0.106	-0.131
Mother born outside Canada	0.271	0.153	0.093	0.089	0.095	0.102	0.093	0.097	0.084	0.104
Mother's age at birth	28.522	26.851	25.073	24.940	25.151	25.352	25.031	25.183	24.851	25.303
First registered for MSP as adult	0.428	0.242	0.297	0.271	0.311	0.254	0.278	0.260	0.334	0.253
Panel D: Education and Childhood										
Ever enrolled in high school	0.375	0.463	0.479	0.493	0.471	0.525	0.508	0.524	0.444	0.487
Ever enrolled in any school	0.432	0.568	0.588	0.602	0.579	0.636	0.614	0.622	0.564	0.596
Did not graduate high school	0.191	0.661	0.779	0.815	0.759	0.739	0.788	0.773	0.795	0.770
Any inclusive education designation	0.098	0.515	0.472	0.509	0.451	0.462	0.478	0.471	0.478	0.485
Intellectual IED	0.029	0.164	0.102	0.116	0.095	0.103	0.106	0.106	0.102	0.088
Behavioural IED	0.058	0.306	0.369	0.396	0.353	0.354	0.372	0.357	0.384	0.396
Physical IED	0.024	0.167	0.094	0.104	0.088	0.097	0.094	0.097	0.091	0.098

Continued on next page

Table E.1 — *continued from previous page*

Variable	Housed	On IA/DA, Housed	Any Homeless	Long Homeless	Short Homeless	NFA 1–2 Mo.	NFA3	NFA3, No Shelter	In Shelter	Homeless Hospital
Other MCFD supervision, ages 12-17	0.022	0.112	0.254	0.282	0.238	0.215	0.255	0.231	0.284	0.264
Any foster care, ages 12-17	0.019	0.131	0.263	0.299	0.242	0.221	0.268	0.244	0.289	0.274
Family received IA/DA, ages 12-17	0.085	0.304	0.387	0.411	0.374	0.375	0.400	0.396	0.388	0.351
Panel E: Health										
Any chronic disease	0.529	0.858	0.854	0.892	0.833	0.872	0.870	0.855	0.839	0.982
Chronic substance use disorder (SUD)	0.060	0.340	0.677	0.733	0.645	0.595	0.681	0.610	0.717	0.890
Chronic mental illness	0.356	0.730	0.705	0.727	0.693	0.749	0.717	0.701	0.691	0.860
Schizophrenia	0.012	0.123	0.169	0.177	0.165	0.138	0.162	0.132	0.183	0.343
MSP costs, excluding ER	646	1,417	2,008	1,766	2,145	1,761	1,772	1,567	1,879	5,485
ER cost ($)	80	266	1,032	1,239	914	647	988	615	1,272	2,783
Hospital inpatient cost ($)	705	3,042	10,043	8,292	11,036	6,314	8,039	6,867	8,320	38,182
Total pharmaceutical cost ($)	635	2,435	2,867	3,087	2,742	2,673	2,833	2,248	3,234	4,510
Pharmacare cost ($)	240	2,011	2,492	2,725	2,359	2,328	2,488	1,957	2,843	3,809
Total government healthcare cost ($)	1,671	6,736	15,574	14,022	16,455	11,049	13,288	11,006	14,314	50,259
Received MSP care	0.779	0.886	0.837	0.847	0.831	0.882	0.848	0.822	0.833	0.981
Visited inpatient	0.092	0.179	0.329	0.299	0.346	0.256	0.281	0.231	0.327	1.000
Emergency room visit	0.154	0.307	0.570	0.594	0.557	0.496	0.559	0.480	0.609	0.898
Number of ER visits	0.258	0.788	2.942	3.653	2.538	1.877	2.885	1.787	3.694	7.350
Treated for head injury	0.026	0.053	0.133	0.145	0.126	0.104	0.126	0.097	0.155	0.249
Substance-use-related treatment	0.021	0.142	0.489	0.520	0.471	0.387	0.474	0.376	0.553	0.838
Treated for mental health disorder	0.165	0.466	0.621	0.627	0.618	0.605	0.610	0.539	0.655	0.936
Panel F: Prescriptions										
Received pharmaceutical treatment for AUD	0.003	0.015	0.037	0.031	0.041	0.031	0.032	0.028	0.040	0.075
Received antidepressant	0.134	0.372	0.326	0.287	0.348	0.412	0.319	0.306	0.326	0.436
Received antipsychotic	0.030	0.222	0.271	0.247	0.284	0.282	0.254	0.214	0.293	0.484
Received benzodiazepine	0.047	0.151	0.121	0.101	0.132	0.145	0.111	0.107	0.120	0.206
Received gabapentinoid	0.027	0.106	0.126	0.115	0.133	0.139	0.118	0.103	0.136	0.208
Received opioid	0.099	0.216	0.254	0.275	0.241	0.241	0.250	0.209	0.284	0.347
Received opioid agonist therapy	0.007	0.077	0.288	0.345	0.256	0.232	0.303	0.232	0.341	0.376
Days supplied: AUD treatment	0.3	1.9	3.4	2.6	3.9	3.2	2.9	2.8	3.4	6.8
Days supplied: antidepressant	41.0	133.9	74.0	60.6	81.5	109.1	71.7	75.3	67.7	96.9
Days supplied: antipsychotic	9.8	93.4	68.8	59.3	74.2	79.6	63.6	58.0	69.8	123.0
Days supplied: benzodiazepine	3.7	23.9	9.9	7.9	11.0	14.2	8.9	9.3	9.1	15.2
Days supplied: gabapentinoid	4.6	23.8	19.4	17.1	20.8	24.5	18.1	17.0	20.0	30.1
Days supplied: opioid	4.9	26.5	24.0	28.7	21.4	21.2	23.8	18.8	27.5	32.3
Days supplied: opioid agonist	1.8	20.6	49.0	54.5	45.9	45.8	51.1	41.5	56.2	57.8
Panel G: Criminal Justice										
Criminal charge, alleged	0.003	0.027	0.206	0.242	0.186	0.173	0.218	0.172	0.242	0.260
Discharged from custody	0.001	0.011	0.117	0.140	0.104	0.122	0.133	0.106	0.132	0.145
Panel H: Mortality										

Continued on next page

Table E.1 — *continued from previous page*

Variable	Housed	On IA/DA, Housed	Any Homeless	Long Homeless	Short Homeless	NFA 1–2 Mo.	NFA3	NFA3, No Shelter	In Shelter	Homeless Hospital
Deceased within 12 months	0.005	0.027	0.053	0.044	0.058	0.041	0.049	0.045	0.052	0.104
Panel I: Other Characteristics										
Childhood neighbourhood income decile (mode)	5.808	4.953	4.611	4.512	4.669	4.746	4.574	4.579	4.607	4.772
Current neighbourhood income decile	5.449	4.091	3.639	3.483	3.731	3.922	3.572	3.730	3.508	3.701
In supportive housing	0.002	0.029	0.064	0.050	0.071	0.043	0.061	0.052	0.070	0.082
Lives in same city as parents	0.761	0.676	0.468	0.434	0.486	0.514	0.463	0.497	0.424	0.464
Parents in different city, still in BC	0.168	0.161	0.248	0.248	0.248	0.261	0.248	0.234	0.268	0.248
Parents deceased or out of province	0.071	0.163	0.285	0.318	0.266	0.224	0.290	0.270	0.308	0.288
In regression sample	0.214	0.270	0.269	0.272	0.268	0.298	0.292	0.312	0.235	0.271
Sample Size										
Unique persons	4,205,464	276,335	71,270	28,017	63,630	34,537	48,289	37,549	39,889	20,809

Note: Sample: BC residents aged 19–64, person-year observations from 2018 to 2023. Values are averages at the person-year level unless otherwise noted. *Not Homeless (All)*: all non-homeless residents. *Not Homeless (On IA/DA)*: IA/DA recipients not classified as homeless. *Any Homeless*: NFA3, in shelter, or homeless in hospital. *Long*: ≥ 7 homeless months in the year. *Short*: <7 homeless months in the year. *NFA 1–2 Mo.*: No Fixed Address for only 1–2 consecutive months. *NFA3*: No Fixed Address for ≥ 3 consecutive months. *NFA3, No Shelter*: NFA3 and not recorded in any shelter. *In Shelter*: at least one night in an emergency shelter. *Homeless Hospital*: hospital inpatient with homelessness diagnosis code. Variables based on childhood records are restricted to cohorts born in 1986 or later, and for education-related variables, also conditional on ever being enrolled.

Table E.2: Outcomes Around First Homelessness Entry, by Event Year

Outcome	$s=-4$	$s=-3$	$s=-2$	$s=-1$	$s=0$	$s=1$	$s=2$
Panel A: Homelessness and Housing							
Any homeless measure	0.000	0.000	0.000	0.000	1.000	0.405	0.346
In shelter	0.000	0.000	0.000	0.000	0.520	0.209	0.189
Homeless in hospital	0.000	0.000	0.000	0.000	0.204	0.062	0.061
Any NFA status	0.000	0.000	0.000	0.000	0.627	0.347	0.295
NFA $\geq$ 3 months (NFA3)	0.000	0.000	0.000	0.000	0.558	0.287	0.241
In supportive housing	0.008	0.010	0.012	0.013	0.034	0.052	0.068
Panel B: Income Support							
Received IA or DA	0.425	0.456	0.489	0.529	0.799	0.748	0.727
Received DA	0.233	0.250	0.268	0.277	0.346	0.388	0.416
IA/DA dollars received ($)	5,047	5,598	6,362	6,838	8,785	8,695	9,147
Panel C: Family and Residential Status							
Family dissolution	0.034	0.031	0.030	0.028	0.036	0.009	0.007
Single	0.674	0.704	0.739	0.853	0.904	0.892	0.875
Resident in province	0.794	0.816	0.843	0.917	1.000	0.948	0.932
Panel D: Healthcare Use and Costs							
Received MSP care	0.816	0.814	0.813	0.795	0.820	0.785	0.784
Visited inpatient	0.162	0.169	0.185	0.227	0.336	0.218	0.219
Emergency room visit	0.363	0.374	0.397	0.453	0.513	0.396	0.388
Number of ER visits	0.980	1.033	1.157	1.536	2.172	1.536	1.513
Treated for head injury	0.073	0.078	0.081	0.093	0.119	0.089	0.089
Substance-use-related treatment	0.218	0.243	0.275	0.329	0.400	0.329	0.335
Treated for mental health disorder	0.447	0.472	0.493	0.525	0.583	0.511	0.511
MSP costs, excluding ER	1,104	1,153	1,207	1,415	2,043	1,341	1,354
ER cost ($)	269	295	350	511	783	548	565
Hospital inpatient cost ($)	2,086	2,368	2,965	5,540	9,995	5,109	5,129
Total pharmaceutical cost ($)	1,377	1,466	1,511	1,558	2,069	2,163	2,348
Pharmacare cost ($)	1,051	1,142	1,188	1,242	1,747	1,843	2,006
Total government healthcare cost ($)	4,510	4,958	5,710	8,707	14,568	8,841	9,054
Panel E: Prescriptions Received							

Continued on next page

Table E.2 — *continued from previous page*

Outcome	$s=-4$	$s=-3$	$s=-2$	$s=-1$	$s=0$	$s=1$	$s=2$
Received pharmaceutical treatment for AUD	0.007	0.011	0.018	0.029	0.040	0.033	0.035
Received antidepressant	0.292	0.303	0.321	0.338	0.348	0.312	0.305
Received antipsychotic	0.171	0.181	0.196	0.222	0.264	0.235	0.237
Received benzodiazepine	0.141	0.137	0.131	0.135	0.134	0.106	0.105
Received gabapentinoid	0.070	0.078	0.088	0.105	0.124	0.112	0.110
Received opioid	0.232	0.220	0.207	0.199	0.220	0.208	0.226
Received opioid agonist therapy	0.095	0.113	0.137	0.166	0.196	0.194	0.206
Panel F: Days Supplied							
Days supplied: AUD treatment	0.5	0.8	1.4	2.3	3.9	3.6	3.9
Days supplied: antidepressant	77.6	80.3	84.4	84.7	85.6	79.6	81.4
Days supplied: antipsychotic	51.7	54.3	56.9	56.1	67.8	66.8	71.5
Days supplied: benzodiazepine	18.7	17.0	15.4	13.4	11.7	9.9	10.4
Days supplied: gabapentinoid	13.0	14.5	16.3	17.1	19.7	19.0	19.5
Days supplied: opioid	21.7	19.2	17.0	15.6	17.1	18.5	22.3
Days supplied: opioid agonist	21.4	24.5	27.6	29.4	34.0	34.4	36.9
Panel G: Criminal Justice							
Criminal charge, alleged	0.105	0.118	0.130	0.162	0.160	0.120	0.112
Discharged from custody	0.043	0.047	0.052	0.064	0.083	0.061	0.058
Panel H: Mortality							
Deceased	0.000	0.000	0.000	0.000	0.024	0.050	0.076
Sample Size							
Observations (alive)	40,559	40,559	40,559	40,559	40,559	39,491	30,583

Note: The table reports averages of each outcome at event year s relative to first entry into homelessness ($s=0$) for the sample of first-time homeless entrants. Outcomes defined as in Table A.1. "Observations (alive)" is the number of individuals observed alive at event year s.

Table E.3: Outcomes Conditional on Entering Homelessness at $s = 0$

Outcome	Likelihood $s = -48$	Likelihood $s = -1$	Bayes Factor $s = -1$
Crime			
Discharged from custody	0.01	0.01	55.2
Criminal charge, alleged	0.02	0.04	51.2
Health			
Hospital inpatient cost ($)	$168	$900	13.8
ER cost ($)	$22	$74	10.3
Number of ER visits	0.08	0.21	9
Total government healthcare cost ($)	$368	$1262	8.4
Emergency room visit	0.06	0.13	6.9
Treated for mental health disorder	0.16	0.25	6.2
Visited inpatient	0.02	0.05	5.2
Treated for head injury	0.01	0.01	5.1
Pharmacare cost ($)	$86	$108	4.9
MSP costs, excluding ER	$92	$180	3.3
Total pharmaceutical cost ($)	$113	$135	2.5
Received MSP care	0.4	0.45	1.4
Substance Use			
Substance-use-related treatment	0.08	0.15	17.5
Received opioid agonist therapy	0.06	0.11	16.9
Days supplied: opioid agonist	1.72	2.69	14.5
Received pharmaceutical treatment for AUD	0.001	0.01	13.1
Days supplied: AUD treatment	0.03	0.27	10.8
Pharmaceuticals			
Received antipsychotic	0.09	0.12	7.3
Days supplied: antipsychotic	4.31	5.18	6
Received gabapentinoid	0.03	0.05	5.7
Days supplied: gabapentinoid	1.05	1.65	4.2
Received benzodiazepine	0.05	0.05	4
Days supplied: benzodiazepine	1.74	1.16	3.5
Received antidepressant	0.13	0.16	3.3
Days supplied: opioid	1.98	1.36	3.1
Received opioid	0.07	0.06	3
Days supplied: antidepressant	6.54	7.73	2.3
Family Type			
Single	0.63	0.84	1.7
Income			
Received IA or DA	0.35	0.46	9.4
IA/DA dollars received ($)	$420	$600	8.7
Received DA	0.21	0.26	7.5
Housing			
In supportive housing	0.01	0.01	4.1

Note: Outcomes at month s are shown for people who become homeless at time $s = 0$. s is defined as months since homeless entry; hence, month $s = -1$ is the month before entering homelessness. Columns 2 and 3 report averages among eventual homeless entrants, $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. Column 4 divides these averages by the corresponding outcome in the rest of the population, $E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$, to obtain the Bayes Factor. For instance, a Bayes Factor of 15 means that homeless entrants are 15 times more likely to experience the outcome than non-entrants in event month s.

Table E.4: Cox Proportional Hazard Model

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
A. Demographics							
Male	1.11***	1.10***	1.13***	1.34***	1.13***	1.06**	1.23***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Family type (base: parent in a couple)							
Single and childless	2.60***	2.57***	2.56***	5.91***	2.95***		2.89***
	(0.15)	(0.15)	(0.15)	(0.27)	(0.17)		(0.18)
Childless couple	1.44***	1.44***	1.41***	1.41***	1.47***		1.85***
	(0.12)	(0.12)	(0.12)	(0.08)	(0.13)		(0.15)
Single parent	1.93***	1.93***	1.96***	4.38***	2.64***		1.61***
	(0.13)	(0.13)	(0.13)	(0.23)	(0.17)		(0.11)
Missing family type	5.95***	1.95**	5.46***	11.34***	7.49***		
	(1.25)	(0.41)	(1.20)	(1.52)	(1.57)		
B. Criminal Justice Involvement							
Alleged to have committed a crime	3.98***	3.96***	3.95***	4.74***	4.94***		2.25***
	(0.19)	(0.19)	(0.19)	(0.21)	(0.24)		(0.09)
Discharged from custody	1.57***	1.56***	1.36***	2.06***	1.77***		1.54***
	(0.12)	(0.12)	(0.11)	(0.14)	(0.13)		(0.08)
C. Medical Interactions							
Treated for head injury	1.19**	1.20**	1.10	1.35***	1.23***		1.10
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)		(0.06)

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
Treated for mental health disorder	1.19***	1.19***	1.13***	1.24***	1.10**		0.78***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)		(0.02)
Treated for substance-use-related issue	1.75***	1.72***	1.67***	1.62***	1.79***		2.06***
	(0.08)	(0.08)	(0.08)	(0.06)	(0.08)		(0.08)
Visited ER	2.13***	2.13***	2.02***	2.52***	2.32***		1.93***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)		(0.05)
Visited inpatient	1.34***	1.32***	1.20***	1.34***	1.30***		1.00
	(0.06)	(0.05)	(0.05)	(0.04)	(0.05)		(0.03)
D. Chronic Disease							
New substance use disorder diagnosis	3.43***	3.43***	3.54***	4.04***	4.67***		1.82***
	(0.28)	(0.28)	(0.30)	(0.31)	(0.38)		(0.14)
Diagnosed with SUD 4+ months ago	4.56***	4.51***	4.58***	4.93***	6.49***		2.63***
	(0.14)	(0.14)	(0.14)	(0.12)	(0.20)		(0.06)
Newly diagnosed with chronic mental illness	2.20***	2.21***	2.06***	2.48***	2.42***		1.31**
	(0.19)	(0.19)	(0.19)	(0.20)	(0.21)		(0.11)
Diagnosed with CMI 4+ months ago	1.58***	1.59***	1.58***	1.56***	1.72***		0.98
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)		(0.02)

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
New schizophrenia diagnosis	2.05***	2.07***	2.05***	1.80***	2.03***		1.68***
	(0.25)	(0.25)	(0.26)	(0.21)	(0.25)		(0.19)
Diagnosed with schizophrenia 4+ months ago	1.52***	1.52***	1.54***	1.28***	1.36***		1.29***
	(0.07)	(0.07)	(0.07)	(0.04)	(0.06)		(0.05)
New diagnosis of other chronic disease	0.97	0.89	0.81	0.73**	0.99		0.76*
	(0.15)	(0.15)	(0.14)	(0.08)	(0.15)		(0.08)
Diagnosed with other chronic disease 4+ months ago	0.93**	0.93**	0.94**	0.94***	0.98		0.85***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.02)
E. Prescriptions Received							
Received AUD treatment	1.27**	1.27**	1.26*	1.19**	1.19*		0.89
	(0.11)	(0.11)	(0.11)	(0.08)	(0.10)		(0.06)
Received antidepressant	1.06*	1.06*	1.04	0.95*	0.98		0.89***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)		(0.02)
Received antipsychotic	1.08*	1.08*	1.07	1.02	1.03		1.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)		(0.03)
Received benzodiazepine	0.93	0.93	0.94	0.89***	0.88**		0.81***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)		(0.03)
Received gabapentinoid	1.13*	1.12	1.20**	1.13***	1.08		1.01
	(0.07)	(0.06)	(0.07)	(0.04)	(0.06)		(0.04)
Received opioid	0.94	0.94	0.94	0.93*	0.95		0.90**

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)		(0.03)
Received opioid agonist therapy	1.29***	1.29***	1.35***	1.09*	1.32***		1.09*
	(0.06)	(0.06)	(0.07)	(0.04)	(0.06)		(0.04)
F. Government Income Support							
New IA spell	2.86***	2.83***	4.06***	5.37***	3.83***		0.18***
	(0.19)	(0.19)	(0.25)	(0.32)	(0.26)		(0.01)
In IA spell that started 4+ months ago	3.30***	3.31***	3.51***	6.42***	4.93***		0.26***
	(0.12)	(0.12)	(0.13)	(0.20)	(0.18)		(0.01)
New DA spell	2.49***	2.52***	2.82***	5.78***	4.44***		0.20***
	(0.30)	(0.31)	(0.34)	(0.58)	(0.52)		(0.01)
In DA spell that started 4+ months ago	1.95***	1.96***	2.09***	3.73***	3.30***		0.18***
	(0.07)	(0.07)	(0.07)	(0.10)	(0.11)		(0.01)
G. Childhood and Family Background							
Any foster care, ages 12–17	1.32***	1.33***	1.32***			1.91***	
	(0.05)	(0.05)	(0.05)			(0.07)	
Other MCFD supervision, ages 12–17	1.26***	1.26***	1.27***			1.66***	
	(0.05)	(0.05)	(0.05)			(0.06)	
Family received IA/DA, ages 12–17	1.39***	1.40***	1.38***			1.69***	
	(0.04)	(0.04)	(0.04)			(0.04)	

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
Birth weight (standardized)	0.98	0.98	0.99			0.99	
	(0.01)	(0.01)	(0.01)			(0.01)	
Parents unmarried at birth	1.52***	1.52***	1.53***			1.91***	
	(0.04)	(0.04)	(0.04)			(0.05)	
Present in BC birth records	0.83***	0.84***	0.83***			0.86***	
	(0.03)	(0.03)	(0.03)			(0.03)	
Childhood neighbourhood income decile (mode, base: decile 10)							
Decile 1 (lowest income)	1.19***	1.18***	1.20***			1.23***	
	(0.06)	(0.06)	(0.06)			(0.06)	
Decile 2	1.05	1.04	1.06			1.08	
	(0.05)	(0.05)	(0.05)			(0.05)	
Decile 3	1.06	1.05	1.06			1.10	
	(0.05)	(0.05)	(0.05)			(0.05)	
Decile 4	1.11*	1.10	1.11*			1.14**	
	(0.06)	(0.06)	(0.06)			(0.06)	
Decile 5	1.04	1.04	1.05			1.07	
	(0.06)	(0.05)	(0.06)			(0.05)	
Decile 6	1.02	1.01	1.02			1.02	
	(0.05)	(0.05)	(0.05)			(0.05)	
Decile 7	0.97	0.96	0.98			1.01	
	(0.05)	(0.05)	(0.05)			(0.05)	
Decile 8	1.06	1.05	1.06			1.09	
	(0.06)	(0.05)	(0.06)			(0.06)	

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
Decile 9	1.02	1.02	1.04			1.05	
	(0.05)	(0.05)	(0.06)			(0.05)	
H. Education							
High school graduation (base: graduated, Dogwood diploma)							
Did not graduate	2.61***	2.59***	2.61***			5.58***	
	(0.08)	(0.08)	(0.08)			(0.15)	
Unknown	2.74***	2.62***	2.75***			3.77***	
	(0.41)	(0.39)	(0.41)			(0.53)	
Inclusive education designation (base: none)							
Behavioural IED	1.12***	1.12***	1.12***			1.87***	
	(0.03)	(0.03)	(0.03)			(0.05)	
Intellectual IED	1.26***	1.25***	1.25***			1.19***	
	(0.05)	(0.05)	(0.05)			(0.05)	
Physical IED	1.21***	1.22***	1.19***			1.56***	
	(0.05)	(0.05)	(0.05)			(0.06)	
I. Current Neighbourhood Income Decile (base: decile 10)							
Decile 1 (lowest income)	1.61***	1.62***	1.59***	2.05***	2.38***		1.36***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.13)		(0.07)
Decile 2	1.37***	1.38***	1.36***	1.65***	1.89***		1.22***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)		(0.07)

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
Decile 3	1.39***	1.40***	1.36***	1.62***	1.84***		1.21***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.10)		(0.07)
Decile 4	1.29***	1.29***	1.27***	1.44***	1.63***		1.11
	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)		(0.07)
Decile 5	1.25***	1.26***	1.24***	1.40***	1.55***		1.12
	(0.07)	(0.08)	(0.07)	(0.07)	(0.09)		(0.07)
Decile 6	1.26***	1.26***	1.25***	1.27***	1.48***		1.14*
	(0.08)	(0.08)	(0.08)	(0.06)	(0.09)		(0.07)
Decile 7	1.20**	1.20**	1.24***	1.29***	1.40***		1.08
	(0.07)	(0.07)	(0.08)	(0.07)	(0.09)		(0.07)
Decile 8	1.26***	1.27***	1.25***	1.26***	1.43***		1.08
	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)		(0.07)
Decile 9	1.15*	1.15*	1.17*	1.13*	1.26***		1.08
	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)		(0.07)
Unknown decile	1.26	1.28	1.44	2.53***	2.44***		1.86*
	(0.32)	(0.32)	(0.34)	(0.52)	(0.61)		(0.58)
J. Local Housing Market							
Median rent in city (standardized)	0.89	0.89	0.93	0.95	0.91		0.96
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)		(0.07)
Missing rental data	1.03	1.04	0.96	0.95	0.95		1.10
	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)		(0.17)
K. Location of Parents (base: Parents in Same City)							

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
Parents in different city, still in BC	1.40***	1.40***	1.41***			1.50***	
	(0.04)	(0.04)	(0.04)			(0.04)	
Parents deceased or out of province	1.46***	1.44***	1.46***			1.53***	
	(0.05)	(0.05)	(0.05)			(0.05)	
L. CMA Fixed Effects (base: Vancouver, CMA 933)							
Rural / No CMA	1.33	1.31	1.50	1.79**	1.86**		1.01
	(0.30)	(0.29)	(0.33)	(0.33)	(0.41)		(0.21)
Small Urban Centres	1.18	1.18	1.31	1.62**	1.60*		1.24
	(0.23)	(0.23)	(0.25)	(0.25)	(0.31)		(0.23)
Kelowna (915)	1.22	1.21	1.30*	1.42***	1.30*		1.09
	(0.13)	(0.13)	(0.14)	(0.12)	(0.14)		(0.11)
Kamloops (925)	1.07	1.06	1.16	1.42**	1.29		1.15
	(0.16)	(0.16)	(0.18)	(0.17)	(0.20)		(0.16)
Chilliwack (930)	0.94	0.93	1.03	1.42*	1.19		1.12
	(0.17)	(0.17)	(0.19)	(0.21)	(0.22)		(0.19)
Abbotsford–Mission (932)	0.88	0.88	0.94	1.14	0.98		1.09
	(0.14)	(0.14)	(0.15)	(0.14)	(0.15)		(0.16)
Victoria (935)	0.88	0.88	0.92	1.06	0.97		1.04
	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)		(0.09)
Nanaimo (938)	0.97	0.98	1.06	1.33*	1.23		1.04
	(0.15)	(0.15)	(0.16)	(0.17)	(0.19)		(0.15)

Continued on next page

Table E.4 — *Continued from previous page*

	(1) Baseline	(2) Incl. BC-Leavers	(3) 2-Month Lag	(4) Expanded	(5) No Childhood	(6) Only Childhood	(7) IA/DA Recipients
CMA unknown	1.65	1.64	1.45	1.11	1.97*		1.12
	(0.55)	(0.55)	(0.47)	(0.30)	(0.66)		(0.41)
M. Year Fixed Effects (base: 2018)							
2019	0.93*	0.93	0.92*	0.83***	0.91**	0.86***	0.88***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
2020	0.88**	0.89**	0.82***	0.69***	0.84***	0.77***	0.86***
	(0.04)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
2021	0.88**	0.89*	0.86**	0.72***	0.83***	0.75***	0.98
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)
2022	0.92	0.95	0.88**	0.73***	0.86***	0.80***	0.92*
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Model Statistics							
Observations (person-months)	35,101,974	35,731,982	35,091,873	77,916,469	35,101,974	35,101,974	2,408,378
Events (first homeless spells)	10,101	10,101	10,048	15,164	10,101	10,101	12,099

Note: This table reports exponentiated coefficients (hazard ratios) from a Cox proportional hazard model of first entry into homelessness. Each coefficient represents the ratio of the monthly hazard for a one-unit change in the covariate, all else equal. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.5: Homelessness per Capita and Median Rent: Regression Results

	(1) Log/log all Regions	(2) Log/log complete only	(3) Level/SD all Regions	(4) Level/SD complete only	(5) Poisson
Panel A: Two-Way Fixed Effects (Unweighted)					
ln(median rent)	-0.5316	-0.5639*			-0.3329*
	(0.2601)	(0.2483)			(0.1629)
SD(median rent)			-0.0003	-0.0004	
			(0.0004)	(0.0006)	
N	618	472	627	475	627
Panel B: Two-Way Fixed Effects (Population-Weighted)					
ln(median rent)	-1.4594*	-1.3905			-0.9775
	(0.5951)	(0.6629)			(0.5019)
SD(median rent)			-0.0018**	-0.0018**	
			(0.0005)	(0.0006)	
N	618	472	627	475	627
Panel C: Long Differences					
Δ ln(rent)	-1.7438*	-0.7867			
	(0.6740)	(1.7960)			
Δ(rent)			-0.0007	-0.0019**	
			(0.0005)	(0.0006)	
N	22	22	22	22	

Notes: Each regression examines whether regions experiencing faster rent growth also see faster growth in homelessness per capita. The outcome is NFA3 homelessness per capita in a region–year. Regions are defined as a Census Metropolitan Area (CMA) or Census Agglomeration (CA). We use the NFA3 count exclusively because it is available consistently over the full sample period. Median one-bedroom rent is from the Canada Mortgage and Housing Corporation's (CMHC) Rental Market Survey. Panels A and B report two-way fixed-effects (TWFE) regressions controlling for year and region fixed effects; identification therefore comes from within-region variation in rent and homelessness over time. Panel C reports long-difference (cross-sectional) regressions at the CMA/CA level. Models (1) and (2) use a log–log specification with ln(NFA3 per capita) as the outcome and ln(median rent) as the explanatory variable. Models (3) and (4) use a levels specification with NFA3 per capita as the outcome and the standard deviation of median rent as the explanatory variable. Models (2) and (4) include only regions for which a complete panel of rent and NFA3 rates is available. Model (5) in Panels A and B is a Poisson pseudo-maximum-likelihood estimator with ln(median rent) as the explanatory variable. Panel B weights observations by CMA/CA population. Standard errors, clustered at the region level, are in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table E.6: Year FEs in Cox Model

	Hazard Ratio	
Year	Year FEs Only	Baseline
2019	0.837***	0.928*
	(0.028)	(0.033)
2020	0.729***	0.880**
	(0.025)	(0.036)
2021	0.691***	0.879**
	(0.024)	(0.042)
2022	0.718***	0.919
	(0.024)	(0.041)

Notes: Each entry is the exponentiated coefficient (hazard ratio) from a Cox proportional hazard model of first entry into homelessness, relative to 2018 (omitted base year). The *Year FEs Only* model includes only calendar-year fixed effects. The *Baseline* model includes the full set of covariates described in Section 5. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.7: LASSO First Homelessness Risk Factors

Variable	**10 Covariates**	**5 Covariates**
Alleged to have committed a crime	5.01	6.49
	(0.240)	(0.318)
Discharged from custody	2.01	2.15
	(0.147)	(0.155)
In IA spell that started 4+ months ago	3.70	3.72
	(0.130)	(0.126)
Treated for substance-use-related issue	3.34	3.55
	(0.107)	(0.114)
Diagnosed with SUD 4+ months ago	5.72	13.22
	(0.177)	(0.357)
Any foster care, ages 12–17	1.77	
	(0.069)	
Other MCFD supervision, ages 12–17	1.48	
	(0.058)	
Did not graduate high school	3.72	
	(0.108)	
In DA spell that started 4+ months ago	2.36	
	(0.078)	
Diagnosed with schizophrenia 4+ months ago	1.83	
	(0.071)	

This table shows the estimated exponentiated coefficients from a Cox proportional hazard model, estimated on a sample of BC-raised individuals from 2018 to 2022, whose covariates were selected by LASSO. We force LASSO to select 10 and 5 covariates, in addition to year effects. As in equation 1, the exponentiated coefficients represent the ratio of the probabilities of first-time homelessness for two person-month observations that differ by one unit in the given covariate (and are otherwise identical). Values greater than 1 indicate increased risk of homelessness. Standard errors in parentheses.