Pathways into Homelessness*

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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. Criminal charges, emergency room visits, and substance use treatment rise sharply in the months before entry. Conditioning on rich individual histories, both childhood disadvantage and acute adult shocks strongly predict entry. We identify a highest-risk group that is 150 times more likely to become homeless than the general population. 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, housing, opioids, crime, machine learning
JEL classification: I32, R31

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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 seven provincial ministries covering health, child welfare, education, social development, 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 as children and fewer than a quarter graduated from high school. In the months before onset of homelessness, criminal charges, emergency room visits, and substance use treatment rise sharply. Conditioning on rich individual histories, both childhood disadvantage and these acute shocks strongly predict entry. We identify a high-risk group that is 150 times more likely to become homeless than the general population, suggesting that entry into homelessness is predictable and potentially preventable.

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). Evidence suggests that relatively modest interventions can prevent entry for those at highest risk (Phillips and Sullivan, 2023, 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. Identifying those at acute risk could allow early interventions for those most likely to benefit.[1]

Second, homelessness is a key marker of vulnerability that we 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 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 determinants sheds light on the rapid aggregate rise in homelessness in British Columbia over the last two decades, a trend shared with many other jurisdictions in North America (Meyer, Wyse, Grunwaldt, Medalia, and Wu,

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

2021). For instance, we find that becoming homeless is strongly associated with both prior criminal justice interactions and substance use disorders. In BC, the rise in homelessness tracks closely with the opioid crisis and the arrival of fentanyl, which suggests that it may have exacerbated the homelessness crisis (see Appendix Figure B.1). Aggregate crime rates, by contrast, have not risen in BC, making crime an unlikely aggregate driver despite its strong individual-level association. Surprisingly, we find no association between living in a CMA where rents increased faster and the risk of entering homelessness, making rising housing costs a less likely explanation for the trend.

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 and short-term disadvantage along nearly every measurable dimension. 51% had interactions with the Ministry of Children and Family Development as children (being under a supervision order or placement in foster care) compared to only 4% of the general population and 23% 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 33% of housed IA/DA recipients. Nearly half of homeless individuals had an inclusive education designation (behavioural, intellectual, or physical) during high school, compared to fewer than one in ten in the housed population. In adulthood, we document profound disparities in health, substance use, and criminal charges. These cross-sectional 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, family dissolution, receiving income or disability assistance, allegedly committing a crime, head injury diagnoses, mental health treatment, and substance abuse treatment, 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 acute shocks 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 matters most. Current economic and health conditions are even more important; conditional on all other risk factors, being on income or disability assistance and having a history of substance use disorder each more than triple the monthly risk of entry. Acute shocks in the preceding three months, such as an alleged crime or substance abuse treatment, carry similarly large risk, meaning that the timing of entry is often predictable. Although these estimates are not necessarily causal, identifying adverse events that consistently precede homelessness enables prediction, 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. It identifies a highest-risk group - the 0.1 percent of the population most at risk - that is 150 times more likely to enter homelessness than the general population. This hazard model assumes each risk factor operates independently. Homelessness, however may result from a combination of shocks, such as a family dissolution compounded by a substance use relapse. To capture these dynamics, we turn to machine learning tools, including penalized maximum likelihood and decision trees, that can handle large sets of interactions between variables. We validate out-of-sample by predicting homeless entry in 2023-2024, and show that XX% of individuals in the highest-risk group do become homeless over the following year.[2] These predictors are observed at points of contact with hospitals, the courts, and social assistance offices, so they are potentially actionable for policymakers targeting early intervention.

Our main contribution is to identify risk factors of homelessness with greater detail, frequency, and comprehensiveness than any prior study. The Australian Journey 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,

[2]The results of these prediction exercises have not yet been approved for release but they will be by the time of the NBER SI.

Wooden, Bevitt, Chigavazira, Greer, Johnson, Killackey, Moschion, Scutella, Tseng, and Watson, 2012, among others) produced pioneering work on trajectories into homelessness. But the Journey 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. They find long-term deprivation but little change in employment or benefit receipt around the year in which they observe homelessness, which they argue implies that homelessness may be difficult to predict from these variables alone (Meyer et al., 2021). Our data differ from theirs in three important dimensions. First, we observe flows into homelessness rather than a stock at a single point in time. This lets us study first entries, timing events precisely relative to onset. Second, we link individuals to childhood records, revealing disadvantages that originate decades before housing loss. Third, our high-frequency administrative data across health, criminal justice, and social assistance reveals severe adverse events accumulating rapidly in the months before entry, a pattern difficult to detect without high-frequency data around first entry.

Our work also advances the pioneering 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. These policy reports focus on implementation rather than on identifying the risk factors that drive prediction. Our contribution is to identify specific risk factors and their relative importance, and to demonstrate the additional predictive value of childhood history that 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.

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 Ministry of Children and Family Development interactions), corrections (custody, community supervision, and criminal charges), and vital statistics (births and deaths). For those born in BC from 1986 onward, 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 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 occurs when income falls below a specified threshold, so we capture the ultimate consequence of employment instability even if we cannot measure it directly.

2.2 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 coverage 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 couch surfing or 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). 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. IA/DA data provide a reliable NFA flag since October 1990. 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 are made aware that a patient has no fixed address.[3] This diagnosis code has been reported since 2001.[4]

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.[5] 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 homelessness flag 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 retain the 14% that remain unlinked in our homelessness counts but cannot track them across other administrative systems.

Our primary measure of homelessness, "Any Measure," flags individuals identified as 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. Figure B.2 illustrates the extent of this overlap. Roughly half of those identified as homeless appear only in NFA records, about one-fifth appear only in shelter records, another fifth appear in both, and only 4% appear only in the hospital records.

We conduct two external validity checks of these administrative homelessness measures. First, we examine whether individuals who entered Supportive and Transitional Housing had self-reported being homeless prior to entry. Appendix Figure B.2 shows that almost 80% of these instances of self-reported homelessness align with our administrative homeless flag during the same period. Second, Appendix Figure B.3 shows that our administrative records qualitatively match time trends in homelessness measured in the annual point-in-time street counts conducted in BC's major cities.

[3]This information typically emerges during patient registration or clinical interactions—for example, when recording the patient's address or taking a medical history.

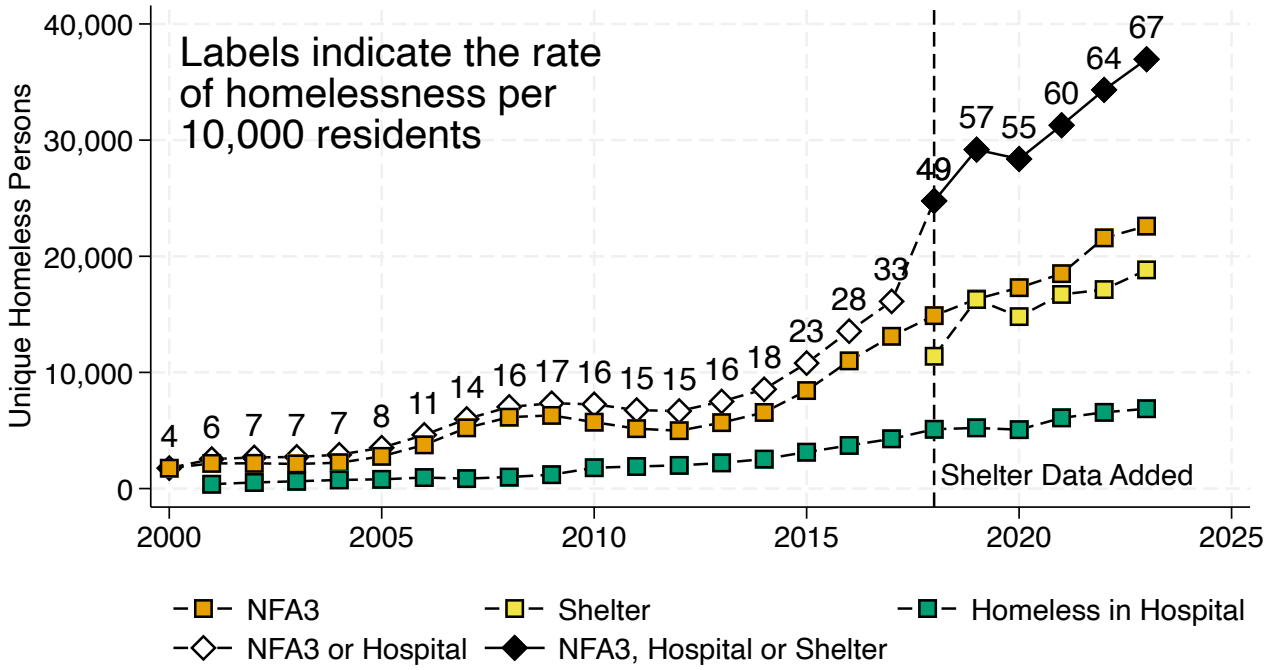
[4]Emergency departments also report a homelessness diagnosis code, but our data does not have it currently.

[5]In recent years, for example, the number of single males in receipt of IA 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 that is less than the maximum benefit amount and liquid assets worth 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.

2.3 *Homelessness trends*

Figure 1 shows the evolution of the homeless population in British Columbia from 2000 to 2023. We present our primary measure (*Any Measure*), for the years after 2018, when our shelter data begins. We also present the NFA3 measure on its own since it provides a consistent measure across all years from 2000 onward. Based on that measure, the number of unique individuals experiencing homelessness in a given year rose by a factor of 20 between 2000 and 2023, which far exceeds population growth. When we add in the shelter data, homelessness rises to over 35,000 unique individuals in 2023, or 0.67% of the provincial population. Those numbers are very similar to those produced by the province (Government of British Columbia, 2024).

Figure 1: Evolution of the Homeless Population, yearly

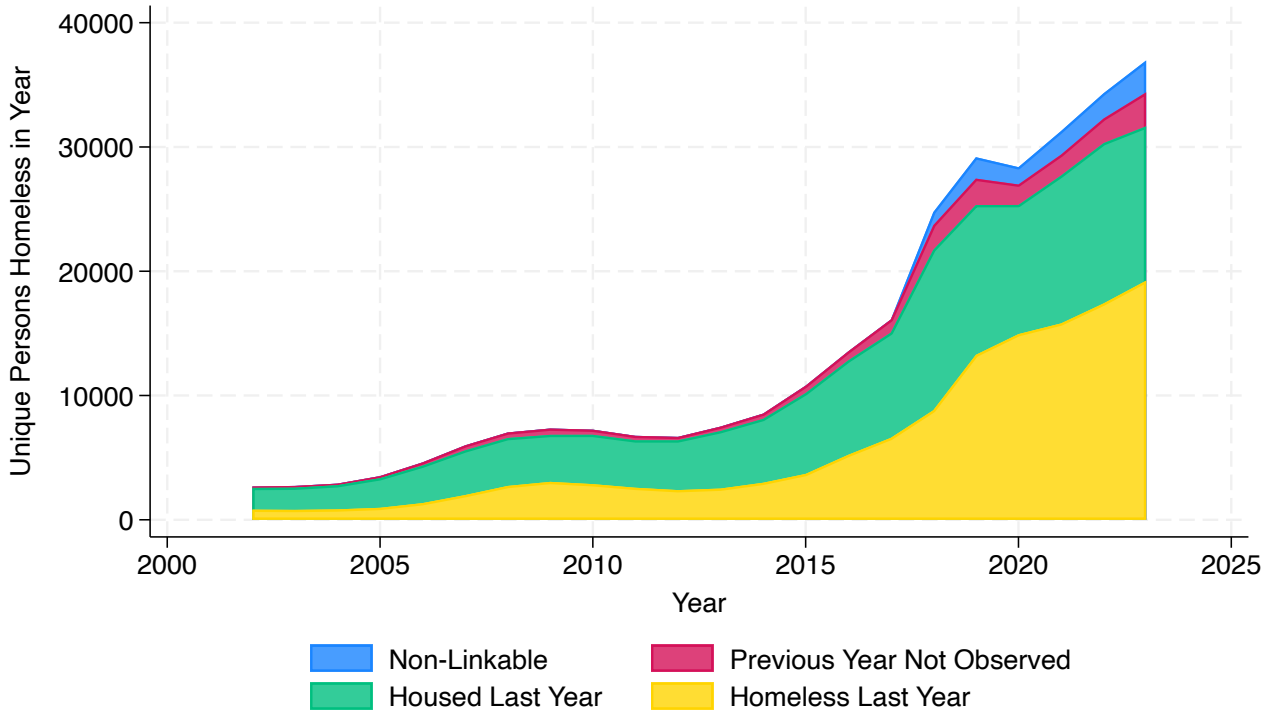


Note: This figure shows trends in the number of people recorded as homeless at some point during each year. The first series is "Any Measure", i.e., three consecutive months with no fixed address (NFA3), in shelter, or homeless in hospital. The other series show each component individually. The vertical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

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 the previous year, and non-linkable identifiers. The yellow region (individuals who were homeless in the prior year) has grown substantially over time, indicating that part of the increase in homelessness rates reflects longer spells. Consistent with this finding, Appendix Figure B.4

shows that the longest NFA spells (7–12 months per year) have grown more rapidly than shorter spells since 2000.

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.

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 surpassed it, and even rural areas experienced substantial increases (Appendix Figure B.5). 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 (individuals who had no fixed address for at least three months in that year, or stayed in a shelter, or were flagged as homeless in a hospital record); the "IA/DA" population (Income Assistance and Disability Assistance 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, 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 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.

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 are similar in age, ranging from 40.8 to 42.7 years.[6] The homeless population has the lowest share of mothers born outside Canada at 9%. This is roughly half the rate of the housed IA/DA population and one-third that of the housed population. Similarly, the homeless population is less likely to be a recent arrival to the province (29.7%) compared to the housed population (43%), as measured by whether they were registered in the province before adulthood. Overall, the homeless population is similar in age but more likely to be male and less likely to be immigrants than the housed population and the merely poor.

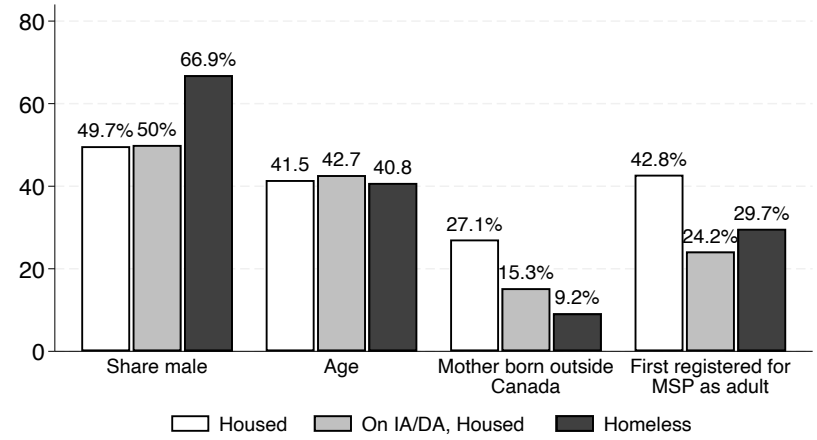
Panel B of Figure 3 displays childhood family stability. We find that 26% of the homeless population interacted with the foster care system between ages 12 and 17, and an additional 25% had other interactions with the Ministry of Children and Family Development, implying that there were some concerns about the child's well-being. In total, a striking 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. These high rates of state interaction are consistent with family structure data showing that only 35% of the homeless population had parents who were married at birth.

These adverse childhood environments parallel the poor educational outcomes reported in Panel C. Only 22.1% of the homeless population graduated from high school, a rate one-third lower than that of the IA/DA population and well below the 81% rate for the housed

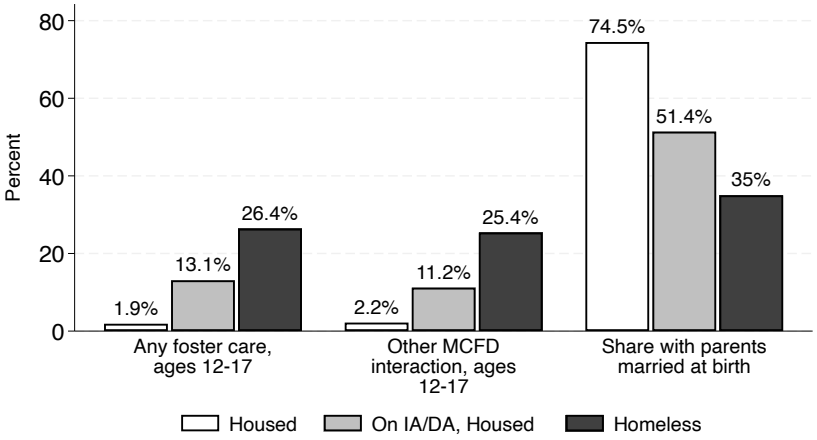
[6] All bar charts in this section report percentage shares, while age is reported in years.

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

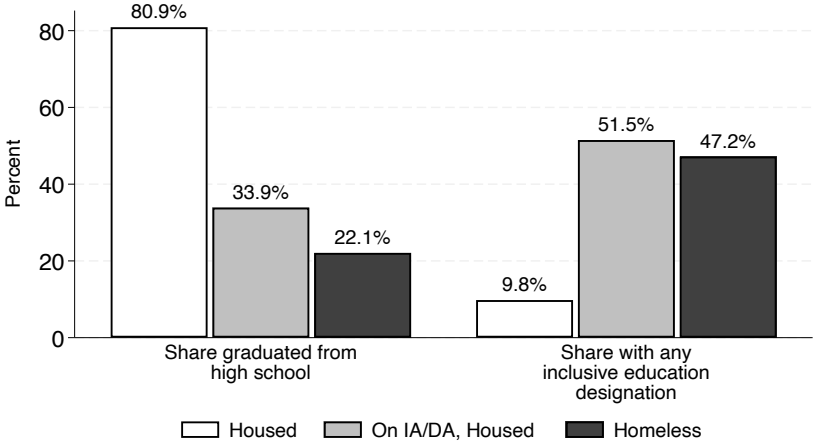
(a) Gender, Age, Immigrant Status



(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 married 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.

population. Consistent with these low graduation rates, 47% of the homeless population had an inclusive education designation, similar to the IA/DA population. Appendix Figure B.6 decomposes these designations and shows that homelessness relates more strongly to behavioural barriers than to physical or intellectual ones. Overall, relative to comparison groups, the homeless population exhibits significant disadvantage through family instability and low human capital.

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

We next consider whether these early disadvantages translate into 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 significantly higher than the housed population. Schizophrenia is most strongly associated with homelessness, affecting 17% of that population compared to 1.2% of the housed population.

Panel B of Figure 4 reports substance use disorder (SUD) statistics. Here, we find much larger gaps than in the chronic disease data. 67% of the homeless population has been diagnosed with a chronic SUD and 49% have received treatment, including 23% receiving opioid agonist therapy. These substance abuse rates are much higher than those of the poor but housed population. Finally, Panel C 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: 19.2% are alleged to have committed a crime in a given year, and 7% have been released from custody.

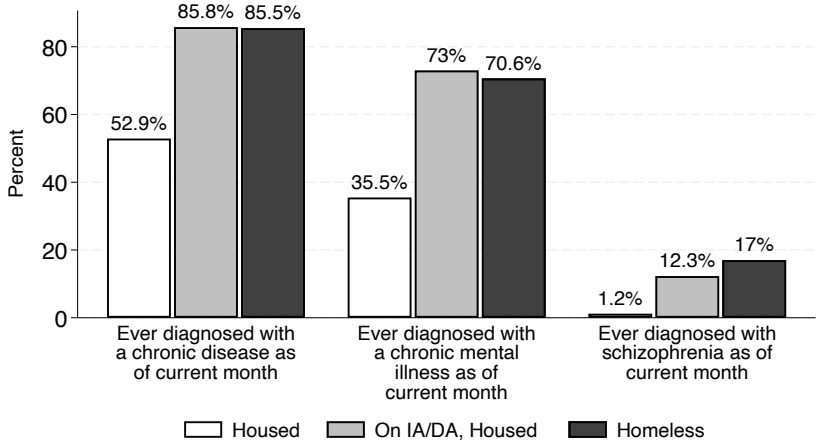
Overall, the homeless population faces challenges across all measured dimensions. We observe particularly large gaps in foster care history, high school graduation, substance abuse, and criminal justice interactions. While childhood characteristics are plausible determinants of homelessness, adult outcomes 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?

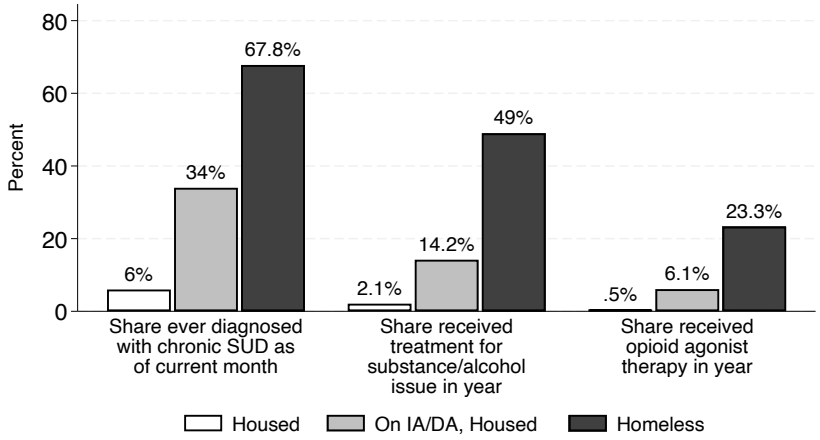
In this section, we describe life trajectories prior to the onset of a first homelessness spell. We track socio-economic, legal, and health outcomes for all adults nineteen years and older who first became homeless between 2018 and 2023. We characterize these trajectories using two moments. The first 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.

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

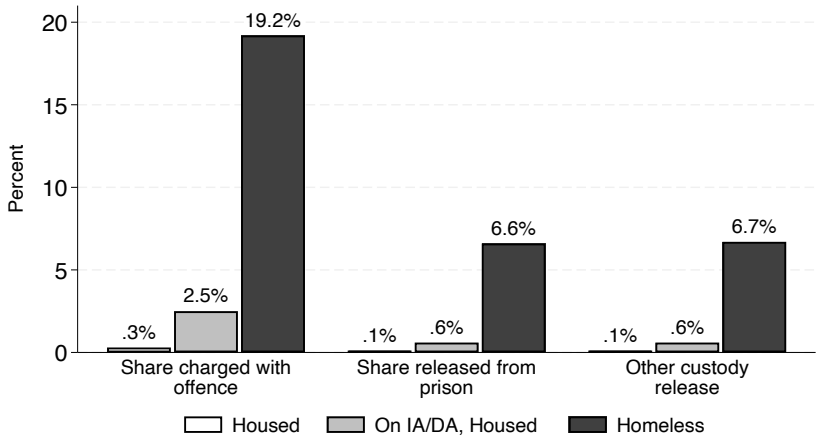
(a) Diagnosed Chronic Disease



(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 diagnosis dates from BC's Chronic Disease Registry. Panel (b) reports rates of chronic substance use disorder (defined as in Panel (a)), hospital or outpatient treatment for substance or alcohol disorders, and receipt of opioid agonist therapy (from prescription records). In Panel (c), 'prison release' and 'other custody release' are defined using BC Corrections movement reason codes.

We also present 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 homelessness (even if it is rare according to the likelihood measure).

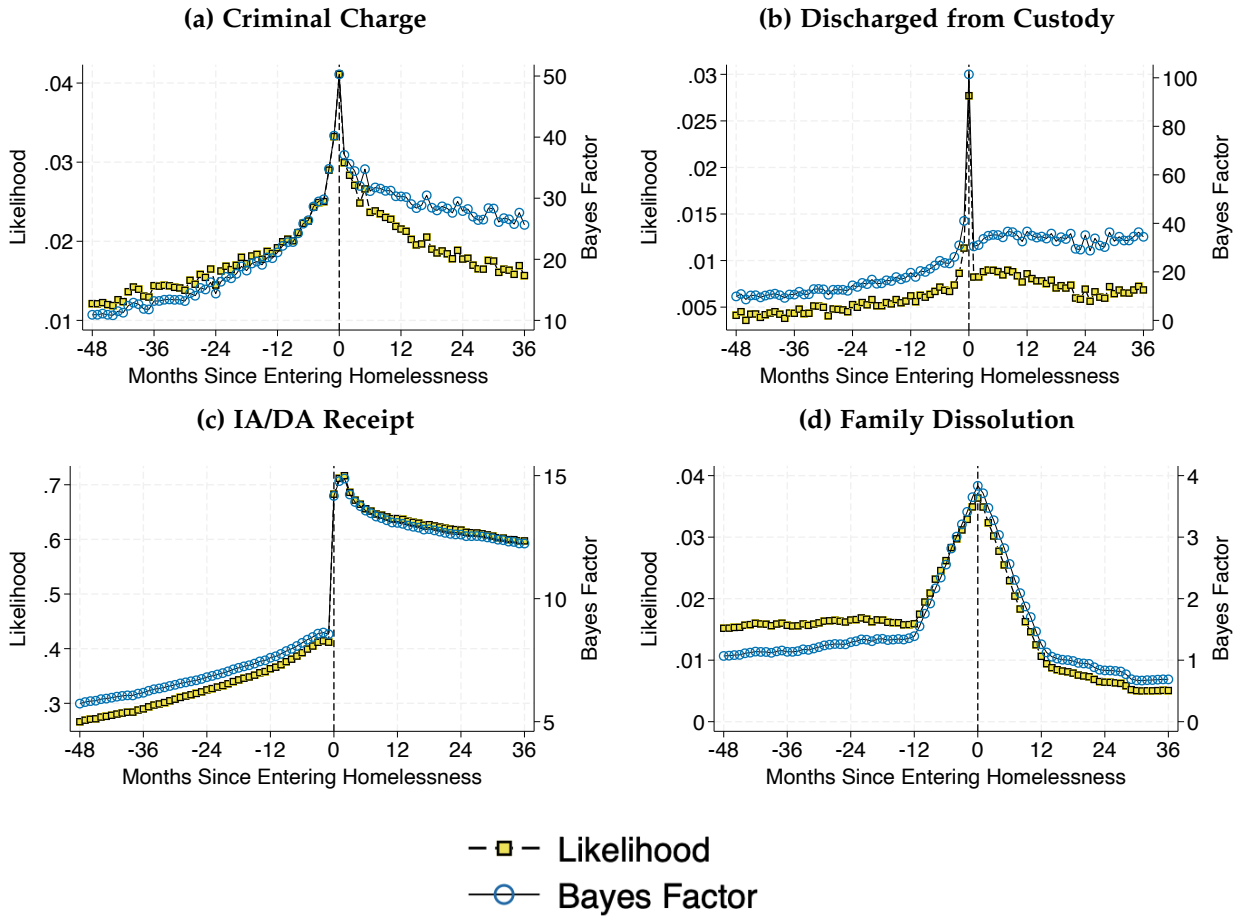
Figure 5 reports these event studies for criminal charges, custody releases, income and disability assistance, and family dissolution. Panel A plots the likelihood and Bayes factor for alleged criminal offences. We find a rapid rise in the likelihood of allegedly committing a crime as people approach homelessness, increasing from 1% four years prior to onset to 3.5% one month prior. The Bayes factor rises to 40 in the month before homelessness, meaning that someone who will become homeless next month is 40 times more likely to have allegedly committed a crime in the current month than someone who will not. We note that alleged crimes spike further in the month of homelessness onset, but events in this month are difficult to interpret; they may be consequences of homelessness or artifacts of how homelessness is recorded when people interact with the court system.[7] 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).

Panels C and D display trends in income and disability assistance receipts, and in family dissolution (defined as having a spouse in the previous year but not in the current year). These events show a gradual rise in likelihood without the sharp acceleration observed for crime. The likelihood of receiving income assistance rises from 30% four years prior to 40% the month before onset. These patterns are consistent with the argument in Meyer et al. (2021) that material deprivation builds slowly. While relationship breakdown is often cited as a key driver of homelessness, the Bayes factor for family dissolution remains moderate at 3 in the month before onset.

Figure 6 reports trajectories for health events: ER visits, head injuries, mental health, and substance use disorder (SUD). All four outcomes show acceleration prior to onset, similar to criminal charges. In Panel A, the likelihood of an ER visit in a month rises from 5% four years prior to 12% a month before onset, with a Bayes factor of 5. Like other outcomes, ER visits spike in the month of onset, reaching 22%. Panel B plots head injuries. While the literature emphasizes Traumatic Brain Injury (TBI) as a correlate of homelessness (Stubbs, Thornton, Sevick, Silverberg, Barr, Honer, and Panenka (2020)), we find it is a rare event (rising to 1.3% a month prior) with a moderate Bayes factor of 5. Panels C and D show that

[7]This is a common issue across all our measures, since an event defined by an interaction with a government system (for example, visiting an ER) could trigger a referral to the IA system, causing an ongoing homelessness spell to be recorded for the first time. For that reason, in our discussions of the event studies, we focus on the month prior to entry into homelessness rather than the month of entry.

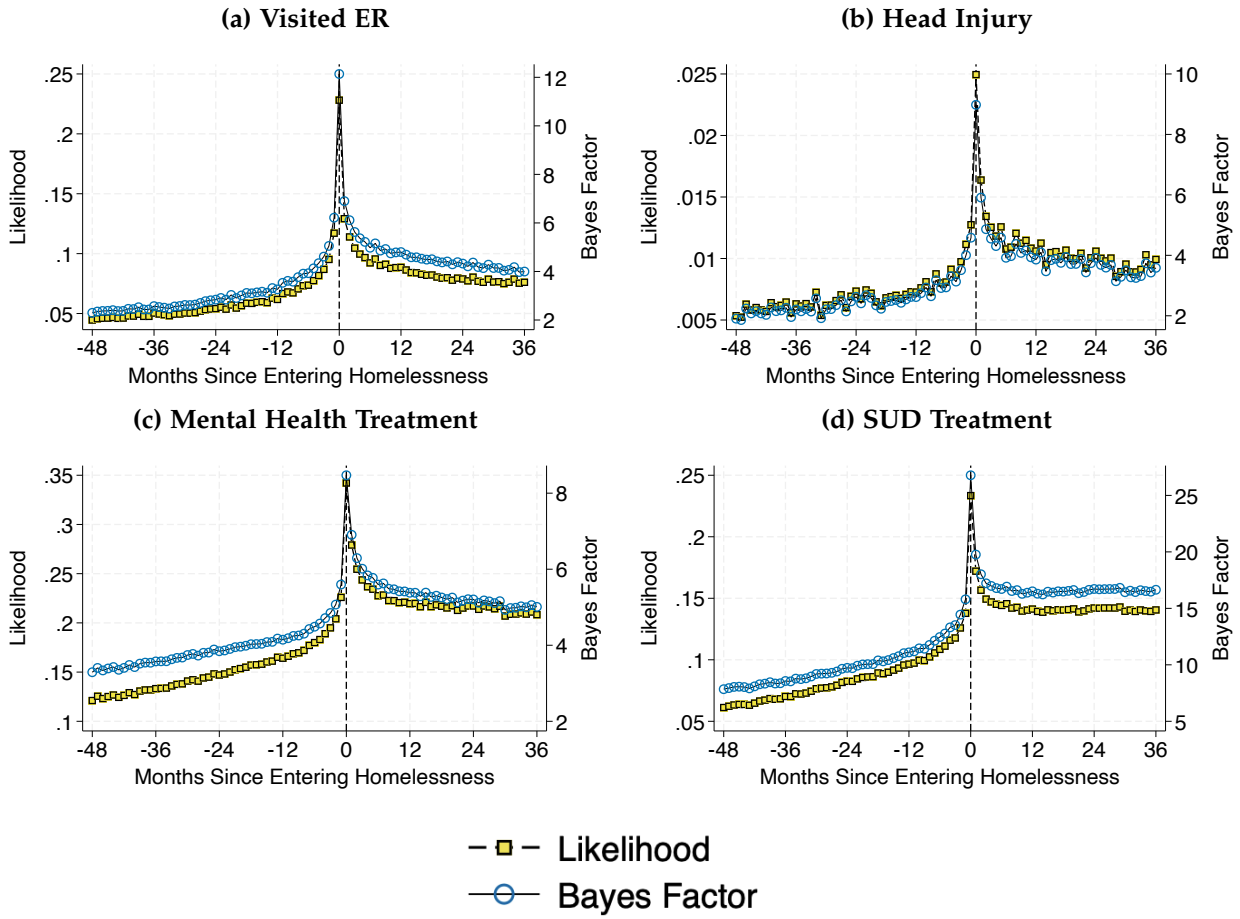
Figure 5: Event Studies: Legal and Socioeconomic Outcomes



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.

chronic health issues, however, are widespread prior to homelessness onset. Receiving mental health treatment is common, with a likelihood rising from 12% four year prior to onset to 22% the month before onset (Bayes factor of 5). Receiving treatment for SUD (including opioid agonist therapy) stands out as both common and highly predictive of homelessness entry. The likelihood rises from 6% four years prior to 14% a month before onset, with a Bayes factor of 15. Appendix Table B.1 reports similar patterns for other health outcomes, such as inpatient visits, suggesting that the events in Figure 6 are representative. Table B.1 also reports likelihood and Bayes Factors for many other outcomes we observe in our data, including for instance, prescriptions by class of drugs (anti-psychotics, benzodiazepines, etc).

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.

Overall, we find that while economic and social indicators build slowly, events related to criminal justice and health 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 precipitate individuals into homelessness. This pattern suggests that homelessness may result from sudden adverse shocks rather than solely long-term deprivation. Notably, these events remain elevated after onset (except for family dissolution), highlighting the persistence of these crises. We do not interpret these spikes as strictly causal in isolation; a criminal charge, for instance, may be just one link in a complex 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 acute shocks in this section imply that specific risk factors drive entry into homelessness. However, given the high correlation between these adverse events, it is a priori unclear which factors are the primary determinants of homelessness onset. To isolate the most important risk factors conditional on rich individual histories, we turn to estimating proportional hazard models.

5. Estimates of Homelessness Risk

In this section, we study the determinants of entry into homelessness using a model that accounts for over a hundred risk factors, including all those discussed in sections 3 and 4. Specifically, we estimate the following Cox proportional hazard model:

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

where $h_{i,\tau}$ is the probability that individual i becomes homeless for the first time at age τ (measured in months), conditional on not having become homeless before. The term h_τ denotes the baseline hazard: the underlying risk of homelessness at age τ. We include calendar-year fixed effects, γ_{year}, to absorb province-wide changes that affect the risk of homelessness. The vector z_i represents time-invariant characteristics, including childhood history, education, and demographics. The vector $x_{i\tau}$ represents time-varying risk factors: cumulative health diagnoses as of month τ, current economic and family status, and acute events occurring within the three months prior to τ.

We report our results as hazard ratios. For dummy variables, such as having a specific medical diagnosis, the hazard ratio is defined as $\exp(\beta)$. 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 in British Columbia starting in 1998. We also require that individuals appear consistently in administrative records during childhood and maintain continuous residency in the province as adults to distinguish homelessness from out-migration.[8] The final estimation sample consists of monthly observations for all individuals meeting these criteria from 2005 through 2023.

Table B.2 presents the full results, as well as specifications defining time-varying factors over six-month and one-year horizons. In Table 1, we report hazard ratios for twenty-two selected variables, including the ten with the highest hazard ratios. Column 1 ranks each variable by the magnitude of its hazard ratio amongst the 103 risk factors we estimate, excluding year and area fixed effects.

Panel A reports hazard ratios for events occurring in the previous three months. These acute shock variables include some of the largest risk factors in our model. Allegedly committing a crime is the most important such event, with a hazard ratio of 3.0, meaning that someone who allegedly commits a crime is three times more likely to become homeless in the following month than someone who hasn't, all else equal. A recent treatment for substance use is the next most important event, with a hazard ratio of 2.73. There are several events with medium-sized hazard ratios between 1.3 and 2.0, including being released from custody or a recent prescription for antipsychotics. These results are consistent with our event studies, which show a sharp rise in the prevalence of acute shocks immediately prior to the onset of homelessness.

Panel B reports common economic, housing, and demographic risk factors prior to entry into homelessness. Having ever been diagnosed with substance abuse disorder (SUD) carries the highest risk factor of any of the variables we consider, with a hazard ratio of about 4. Other chronic health conditions like mental illness and schizophrenia have sizeable but smaller hazard ratios around 1.6. Receipt of IA has a hazard ratio of 3.4, the second highest of any variable. This large hazard ratio is consistent with homelessness being a state of extreme poverty.[9] Receipt of DA doubles the hazard of homelessness, as do being a single parent or being single and childless. Higher median rent in one's metro area is not associated with higher homelessness risk. Given the inclusion of area fixed effects, this coefficient captures within-city variation over time, suggesting that rising rents alone may not be the

[8]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 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 that 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 $t+3$.

[9]We interpret this magnitude with caution. Because designation as having "no fixed address" (NFA) within the Income Assistance system is one of the ways we identify homelessness in our data, being on IA mechanically increases the probability of detection.

Table 1: Estimates of First Homelessness Risk Factors

Rank	Panel / Variable	Hazard Ratio
Panel A: Recent Acute Events (Past 3 Months)		
3	Allegedly Committed a Crime	3.00
5	Substance-Use-Related Medical Treatment	2.73
9	Prison Release	1.81
21	Received Antipsychotic Prescription	1.31
23	Family Dissolution	1.25
Panel B: Current Economics, Health, Housing & Demographics		
–	Median Rent in City (ln)	0.24
1	Chronic Substance Use Disorder	4.02
2	Received IA	3.38
6	Single, Childless	2.11
7	Received DA	2.01
8	Single Parent	1.90
11	Neighbourhood in Lowest Income Decile	1.68
12	Chronic Mental Illness	1.64
16	Schizophrenia	1.51
34	Male	1.14
Panel C: Childhood & Education		
4	Did Not Graduate High School	2.76
14	Parents Unmarried at Birth	1.55
15	Any Foster Care Ages 12–17	1.55
27	Non-Foster-Care MCFD Supervision, Ages 12–17	1.24
31	Inclusive Education Designation: Behavioural, Ages 12–17	1.17
39	Birth Weight (SD) – *not significant at 95% level*	0.98

Notes: The table reports hazard ratios from equation (1) for selected variables, estimated on a sample of BC-raised individuals from 2005 to 2023. The table highlights the ten largest risk factors. Hazard ratios in Column 3 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 Column 1, "rank" orders all significant predictors ($p < 0.05$) by the magnitude of their hazard ratios.

key driver of entry into homelessness in BC.

Panel C turns to childhood and education characteristics. People who fail to graduate from high school are 2.8 times more likely to become homeless, the fourth largest ratio we observe. Other education and childhood outcomes have smaller but sizeable impacts. Having parents who were unmarried at birth, a history of teen foster care, and growing up in a neighbourhood in the bottom decile of the income distribution all have hazard ratios around 1.6. While suggestive of the importance of early-life family stability, the estimated impact of foster care is notably smaller than the raw over-representation of former youth in care within the homeless population. This suggests that foster care correlates with many other risk factors. Other childhood factors, such as contact with child protection services (MCFD) and identified behavioural needs in school, have smaller hazard ratios of around 1.2. Birth weight, which is frequently cited as a correlate of negative outcomes later in life, has no impact on the probability of becoming homeless after controlling for all other risk factors. The hazard ratio for males is close to one, despite men making up two-thirds of the homeless population. This implies that the higher rate of homelessness among men is mostly explained by the risk factors in our model.

Finally, Table B.2 also reports area fixed effects. Conditional on individual characteristics, homelessness risk is highest in Vancouver. Kelowna and Abbotsford, the second- and fourth-largest cities in BC, are statistically indistinguishable from Vancouver, while Victoria and smaller municipalities have significantly lower hazard ratios. This pattern contrasts with the raw data, where Vancouver's per-capita homelessness rate is below the provincial average (Figure B.5). The reversal implies that compositional differences in individual risk factors across cities mask Vancouver's higher conditional risk of entry.

Overall, we identify powerful risk factors across all three categories: acute shocks immediately prior to onset, current economic conditions, and childhood history. The importance of acute shocks, in particular, implies that the timing of homelessness entry is predictable. We turn to such predictions in the next section.

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 cumulative risk for the most disadvantaged individuals remains extreme. For instance, consider a male with background characteristics common among the homeless population: receiving IA, failed to graduate high school, and had unmarried parents. Combining these pre-existing disadvantages with a history of SUD and a recent acute shock (a criminal charge) results in a cumulative hazard ratio of approximately 200 ($4 \times 3 \times 3.4 \times 2.8 \times 1.6 \times 1.1$) relative to the general population. We now turn to using this model to predict who becomes homeless, and verify these predictions out of sample. We then introduce machine learning methods to account for the possibility that these risk factors interact in non-linear ways, for instance,

that the combined impact of crime and substance use differs from their independent multiplicative effect.

6. Predicting entry into homelessness

We have shown that homelessness is preceded by systematic risk factors, including acute shocks immediately prior to entry. Even without establishing a strict causal chain, our understanding of these risk factors can guide early intervention by predicting when entry will occur. Such interventions, however, are often only financially viable if targeted accurately because housing support is so expensive. In this section, we use lifetime risk factors—both from childhood and more recent—to predict future homelessness out of sample. We focus on predictive accuracy at the very top of the risk distribution, where early intervention is most likely to be cost-effective. We describe our methodology below; the *final out-of-sample results are pending disclosure approval and will be available before presentation*.

In all our predictions, we reserve the 24 months of data from January 2023 through the end of 2024 as a test sample. We first predict entry into homelessness using the simple hazard model from section 5. We keep the same specification and sample of British Columbia natives observed since childhood, but we estimate the model using data only up to December 2022. Using the estimated coefficients, we then predict the hazard ratio for each person-month in 2023 and 2024, conditional on not yet having experienced homelessness. These predictions rely on their history at that specific time, but apply parameters estimated strictly prior to the test period. This exercise mirrors the challenge faced by a policymaker intervening in real time to support those most at risk.

Next, we rank each person-month by its predicted hazard ratio and divide the sample into 1000 bins, with each bin containing 0.1 percent of the population or XX person-months. We then compute the actual share of individuals within each bin who become homeless in that specific month. Figure XX reports these results. The horizontal axis displays the predicted hazard ratio for each bin, which reaches up to 150 in the highest risk bin. These high ratios reflect histories of deep disadvantage, typically involving poor childhood outcomes, current economic and health challenges, and recent acute shocks. The vertical axis displays the actual probability that individuals in the bin become homeless in that month. The plotted line is strictly increasing, so there is a tight correspondence between a high predicted hazard ratio and a high actual probability of becoming homeless. In fact, the realized hazard ratio in the top bin is XX, closely matching the predicted ratio of XX. The realized probability of becoming homeless in the next month for this top bin is X percent.

This realized monthly probability is relatively small because the baseline risk of entering homelessness in any single month is very low. To provide a clearer picture of long term risk, Figure X also plots the share of individuals in these same bins who become homeless for the

first time within the next three, six, and twelve months. We find that in our top bin, which represents 0.1% of the sample, XX% of individuals become homeless over the following year. While our prediction exercise prioritizes precision, we note that this top bin accounts for XX% of all new homelessness entries. Expanding this to the top five bins, representing 0.5% of the population, captures X% of all entries. This confirms that the prediction exercise is precise while maintaining a reasonable ability to capture a broad share of the at-risk population.

This analysis restricted the sample to individuals young enough to have been in BC since the data begins. This allows us to measure early childhood risks. Most policy applications, however, require evaluating the entire adult population. In Appendix XX, we replicate our predictions for all adults continuously present in the province since 2018. This expanded sample covers more than XX% of the adult population, but requires dropping the childhood variables. The top risk bin yields a hazard ratio of XX and a one-year predicted probability of XX%, which is only slightly lower than that in our BC-raised sample. That homelessness remains almost as predictable without childhood data shows that current conditions and recent events reflect much of the disadvantage that originates in childhood.

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 acute shocks in adulthood: criminal charges, substance use disorder treatment, and custody releases 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 chronic substance use disorder, income assistance receipt, being recently charged with an offence, and failure to graduate from high school as the most important risk factors, with hazard ratios exceeding 2.5.

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 0.1 percent of the population by predicted risk, that is 150 times more likely to enter homelessness than the general population. This concentration of risk makes targeted early intervention feasible and potentially cost-effective.

Our findings also speak to the limits of broad-based prevention. The province already provides universal income assistance to anyone in need, the kind of cash support that US-based prevention programs are testing as an intervention. Yet homelessness has risen sharply. This suggests that a broad safety net may not be sufficient to prevent entry when individuals face the acute disadvantages we document. Effective prevention may require targeted responses to these specific shocks.

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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 has a residential address or is flagged as having "no fixed address" (NFA). The NFA designation is recorded by caseworkers and 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, procedures, length of stay, and resource intensity weights used to calculate costs. This database also contains International Classification of Diseases (ICD) codes that allow us to identify patients flagged as homeless during their hospital stay.

Medical Services Plan (MSP) Outpatient
Fee-for-service billing records for physician visits and outpatient services, including diagnosis codes that allow identification of substance use disorder treatment, mental health treatment, and head injury treatment.

Chronic Disease Registry
Provincial registry recording first diagnosis dates for chronic conditions. This includes anxiety, depression, schizophrenia, substance use disorder, and other chronic diseases.

PharmaNet
Covers all prescriptions dispensed at BC 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 agonist therapy,

antipsychotics, antidepressants, benzodiazepines, gabapentinoids, and alcohol use disorder treatments.

National Ambulatory Care Reporting System (NACRS)
Information on all emergency department visits from 2011 to 2023.

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 were homeless prior to entry.

A.1.4 Education Data

The K-12 Student Demographics and Achievement records contain annual enrollment data, including school attended, grade level, graduation outcomes, and Inclusive Education Designation (IEDs). IEDs are categorized as behavioural, intellectual, or physical designations. These records are available for individuals born in 1986 or later.

A.1.5 Child Welfare Data

The Child Welfare Program database records interactions with the Ministry of Children and Family Development (MCFD) between 1985 and 2025. 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 interactions. 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 (prison sentences and discharges) and community supervision (probation and conditional sentences) from 2001 to 2023. The movements file records the dates of entry into and exit from custody, along with the reasons for movement (e.g., "Released to Parole," "Sentence/Supervision End," "Released at Court"). We also observe dates of alleged criminal offences leading to BC Corrections involvement. Federal penitentiary sentences are excluded.

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). The BC Vital Events database provides birth records (for those born in BC from 1986 onward), including the mother's age at birth, parents' marital status, and birth weight, as well as death records. 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. **NFA (No Fixed Address)**: Appearing in IA/DA records with no fixed address for any duration.
2. **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.
3. **Shelter**: Appearing in emergency shelter records for at least one night.
4. **Homeless Hospital**: Appearing as a hospital inpatient with a homelessness diagnosis code. Hospitals in Canada are required to assign the International Classification of Diseases (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, pp. 626–627). Homelessness is defined according to the Canadian Observatory on Homelessness criteria: unsheltered, emergency sheltered, or provisionally accommodated.
5. **BC Government Measure**: Either NFA3 or In Shelter. This is the official provincial measure.
6. **Any Measure (Primary)**: NFA3, In Shelter, or Homeless Hospital. This is our main homelessness measure.
7. **Homeless Before Supportive Housing**: Recorded as homeless prior to supportive housing entry. Used for robustness checks.

A.3 Sample Construction

A.3.1 Main Descriptive Analysis Sample

For descriptive analyses, 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 (those not beginning with "F"), except for shelter users from 2018 onward.

A.3.2 Cox Proportional Hazards Regression and Prediction Exercise

For the Cox proportional hazards analysis, 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 age 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 and Sample	Category	Coverage
Average Childhood Neighbourhood Decile	Average neighbourhood income decile from ages 9-17, conditional on being present in BC for at least 7 of those years, and born in 1986 or later	Childhood	1986–2025
Parents Married at Birth	Conditional on appearing in birth records	Childhood	1986–2025
Age of Mother at Birth	Conditional on appearing in birth records	Childhood	1986–2025
Birth Weight	Standardized to mean 0 and standard deviation 1. Conditional on appearing in birth records.	Childhood	1986–2025
Foster Care Teen	Any foster care between ages 12–17. Conditional on being born in 1986 or later, and appearing in the enrollment records at any point between ages 12-17.	Childhood	1986–2025
MCFD File Other	Other MCFD Interaction, ages 12–17. Conditional on being born in 1986 or later, and appearing in the enrollment records at any point between ages 12-17.	Childhood	1986–2025
Received IA/DA Between Ages 12–17	Conditional on being born in 1986 or later, and appearing in the enrollment records at any point between ages 12-17.	Childhood	1986–2025

Continued on next page

Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Graduated from High School (Dogwood)	Conditional on appearing in the K12 enrollment records, age 14-18.	Education	1986–2025
Inclusive Education Designation: Behavioural	Any behavioural IED in K12 enrollment records. Conditional on appearing in the K12 enrollment records and being born in 1986 or later.	Education	1986–2025
Inclusive Education Designation: Intellectual	Any intellectual IED in K12 enrollment records. Conditional on appearing in the K12 enrollment records and being born in 1986 or later.	Education	1986–2025
Inclusive Education Designation: Physical	Any physical IED in K12 enrollment records. Conditional on appearing in the K12 enrollment records and being born in 1986 or later.	Education	1986–2025
Any Inclusive Education Designation	Any behavioural, intellectual or physical IED in K12 enrollment records. Conditional on appearing in the K12 enrollment records and being born in 1986 or later.	Education	1986–2025
Charged with Offence	Received criminal charge leading to BC Corrections supervision/involvement. Fines and other charges without conditions to report are excluded. We use the "offence date" when recorded; if the offence date is missing, we use the date the court issued the authority document associated with the charge.	Corrections	2001-2025
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	2001-2025
Prison Release	Appeared in the BC Corrections movements files with one of the following movement reasons: 'Released to Parole' or 'Sentence/Supervision End'. Individuals with custody group code "FED" are excluded.	Corrections	2001-2025
Other Custody Release	Appeared in the BC Corrections movements files with one of the following movement reasons: 'Released at Court', 'Released to Bail', 'Released to Conditional Sentence', 'Remandee Released-Time Served'. Individuals with custody group code "FED" are excluded.	Corrections	2001-2025

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Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Male	Drawn from MSP client roster demographics file (or IA, shelter, or supportive housing records if missing)	Demographics	1999-2025
Break-Up	Defined among people not flagged as dependents. From one year to next, did the individual change from having a spouse on their MSP contract to not having one.	Demographics	1999-2025
Childless in a Couple	Inferred from MSP contract	Demographics	1999-2025
Parent in a Couple	Inferred from MSP contract	Demographics	1999-2025
Single and Childless	Inferred from MSP contract	Demographics	1999-2025
Single Parent	Inferred from MSP contract	Demographics	1999-2025
Unknown Family Type	Based on MSP contract	Demographics	1999-2025
Mother Born Outside Canada	Based on data in birth records (and thus conditional on appearing in the BC birth records).	Demographics	1986–2025
Immigrant	First registered on an MSP contract at age 18 or older. Only defined for people younger than 50 to ensure that, if they had been residing in the province prior to age 18, they would have been observable in administrative records at that time.	Demographics	1999-2025
Age	Based on birth date in MSP client roster demographics file (or IA/shelter/supportive housing data if missing)	Demographics	1999-2025
Received DA	From SDPR records	Gov't Support	2001–2025
Received IA	From SDPR records	Gov't Support	2001–2025
Dollars of IA/DA Received	From SDPR records	Gov't Support	2001–2025
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	1986-2025
Neighbourhood Income Decile FEs	Neighbourhood income decile	Geography	2016-2021
Natural Log of Median Rent	Within CMA/CA. Calculated from CMHC data for 1-Bedroom apartments. Inflation-adjusted.	Rental	2000-2025
Vacancy Rate	Within CMA/CA. Calculated from CMHC data for 1-Bedroom apartments.	Rental	2000-2025

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Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
Chronic Mental Illness	Ever diagnosed with anxiety or depression as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2025
Schizophrenia	Ever diagnosed with schizophrenia as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2025
Chronic Substance Use Disorder	Ever diagnosed with substance use disorder as of current month. Based on first diagnosis date in chronic disease registry.	Health	1992-2025
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	1992-2025
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	1992-2025
Treated for SUD	Received MSP treatment for substance use disorder. Defined using diagnosis codes starting in 291, 292, 303, 304, and 305.	Health	1990-2025
Treated for Mental Health Diagnosis	Received MSP treatment with diagnosis code starting in 290-319.	Health	1990-2025
Treated for Head Injury	Received MSP treatment with diagnosis code starting in 800, 801, 803, 804, 850-854, 870-873 or 959.	Health	1990-2025
Received Inpatient Care	Appeared in the hospital discharge abstract database.	Health	2001-2025
Visited Emergency Room	Appeared in National Ambulatory Care Reporting System	Health	2011-2025
Received MSP-billed care	Appeared in MSP treatment records	Health	1990-2025
Government Healthcare Cost	Sum of inpatient, emergency room, MSP-billed care, and pharmacare costs	Health	2001-2025
Hospital Inpatient Costs	Product of resource intensity weighting and cost per weighted case	Health	2001-2025
Pharmaceutical Costs	Total pharmaceutical costs associated with dispensations in the year	Health	2001-2025

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Table A.1 – *Continued from previous page*

Variable	Description and Sample	Category	Coverage
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	2001-2025
Received Antidepressant	Identified by matching DIN to ATC code N06A. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2025
Received Antipsychotic	Identified by matching DIN to ATC code N05A. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2025
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	2001-2025
Received Gabapentinoid	Identified by matching DIN to ATC code N02BF. We also include products in this category that are tracked using PINs.	Prescriptions	2001-2025
Received Opioid	Identified by matching DIN to ATC codes N02A, R05DA and R05FA. No corresponding PINs. Opioid anesthetics (N01AH) are not included.	Prescriptions	2001-2025
Received Opioid Agonist	Identified by matching DIN to ATC codes, or by using PIN.	Prescriptions	2001-2025
Resident	Appeared in any administrative data file during the year.	Other	1986-2025
Dead	Month of observation is later than or equal to the month of death recorded in vital statistics.	Other	1985-2025

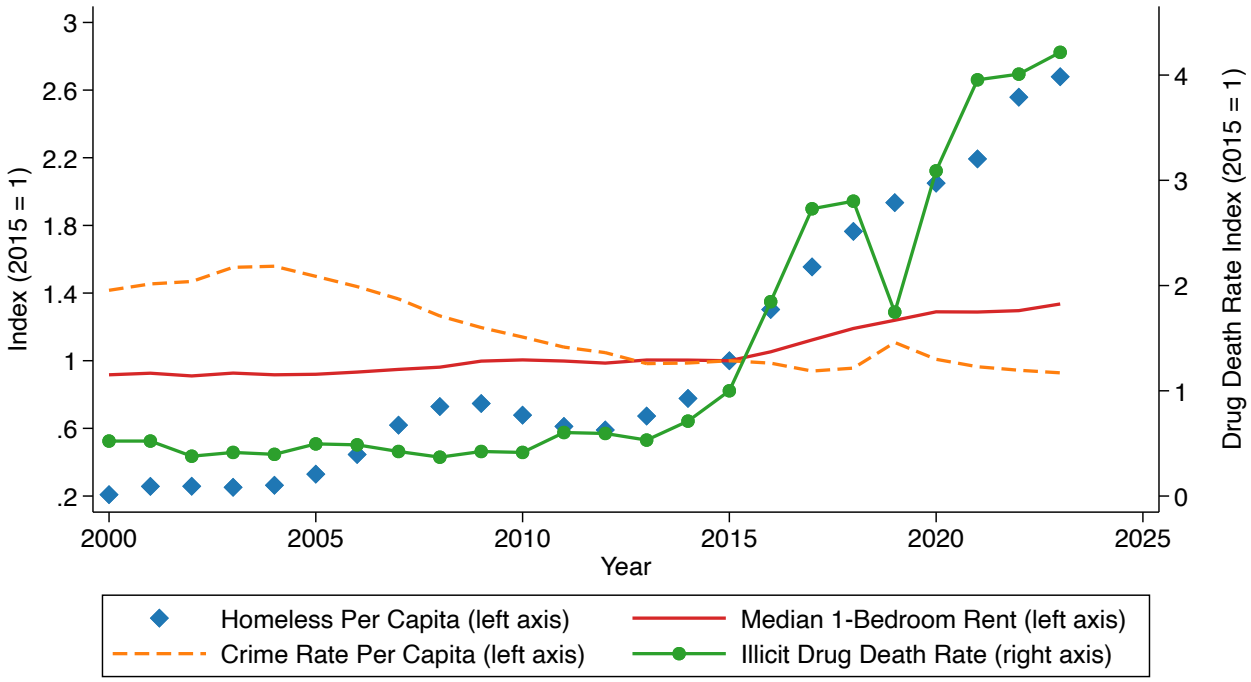
A.5 Data Citations

- 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 2024.
- 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] (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.

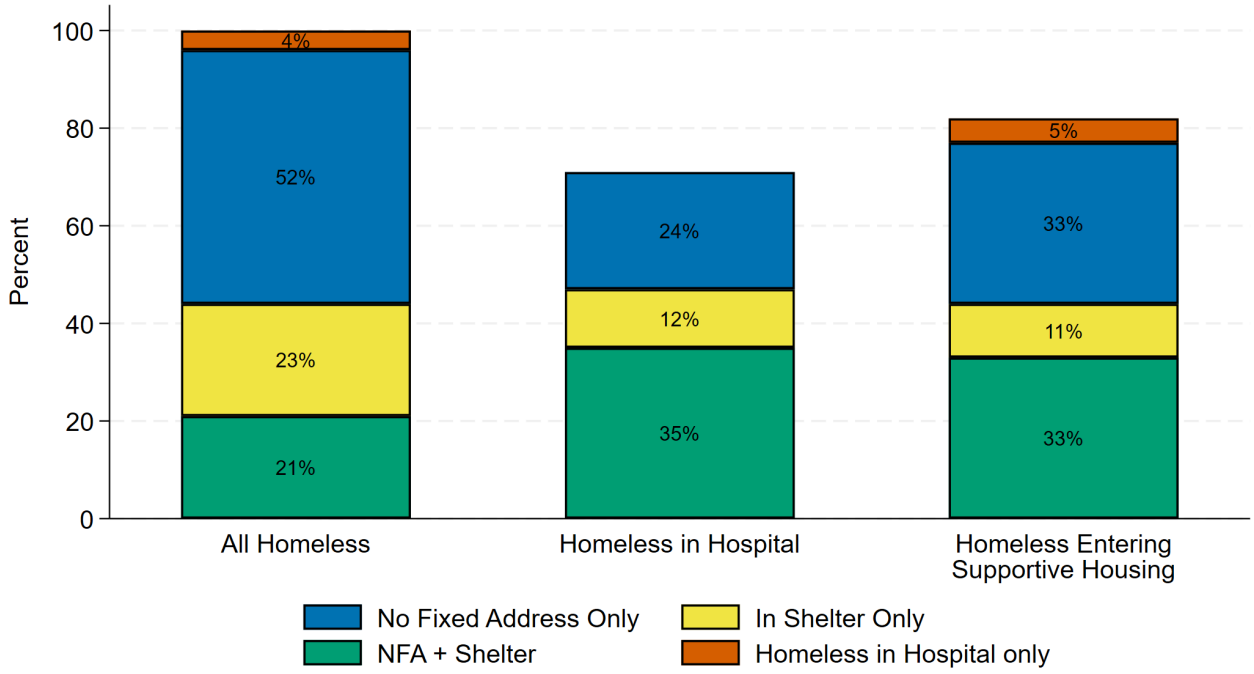
B. Supplemental Results

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



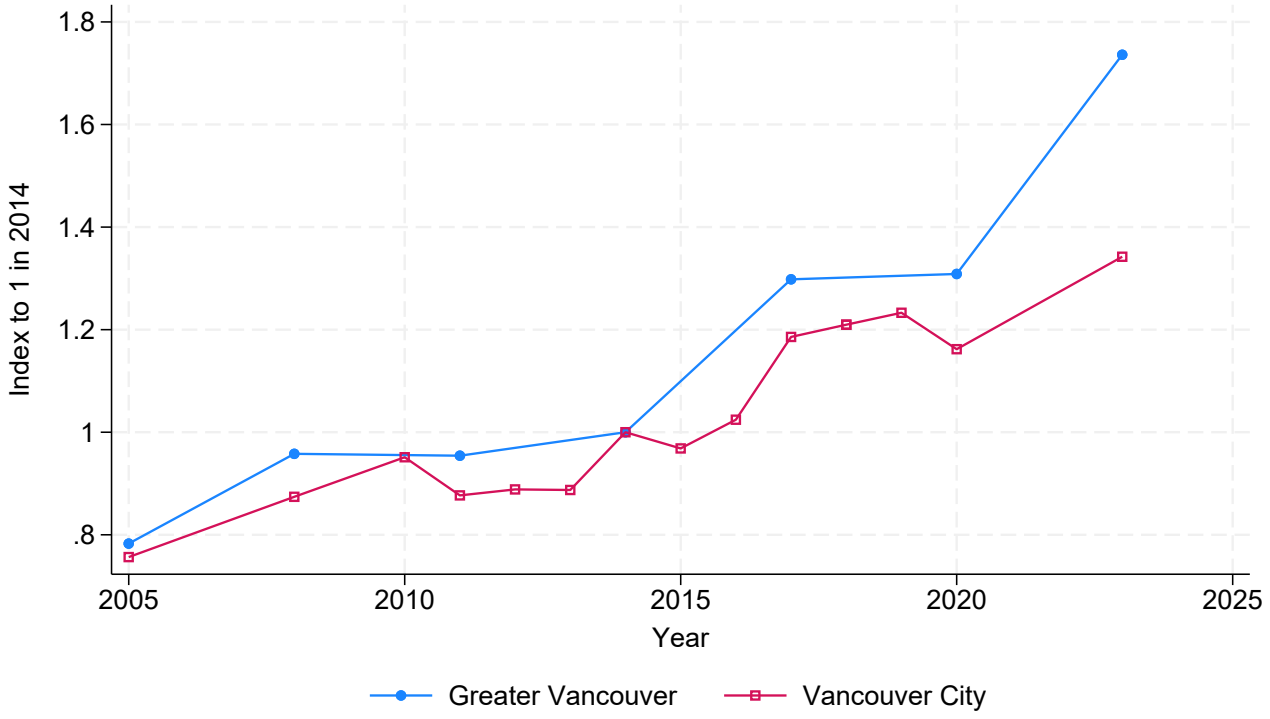
Note: This figure presents the evolution of the homelessness rate along potential aggregate drivers. Homelessness per capita is calculated as the number of unique individuals who were flagged as having no fixed address in the IA/DA for 3 consecutive months, divided by the population that year. All series are indexed to 1 in 2015. The illicit drug death rate uses the right axis.
Source: Statistics Canada. Table 35-10-0184-01 Incident-based crime statistics, by detailed violations, police services in British Columbia;
Canada Mortgage and Housing Corporation Rental Market Survey (https://www03.cmhc-schl.gc.ca/hmip-pimh/en/TableMapChartTableMapChart/59/2/British%20Columbia);
Drug Toxicity Deaths: British Columbia Vital Statistics.

Figure B.2: Decomposition of Homeless Population by Measure and Validation Checks.



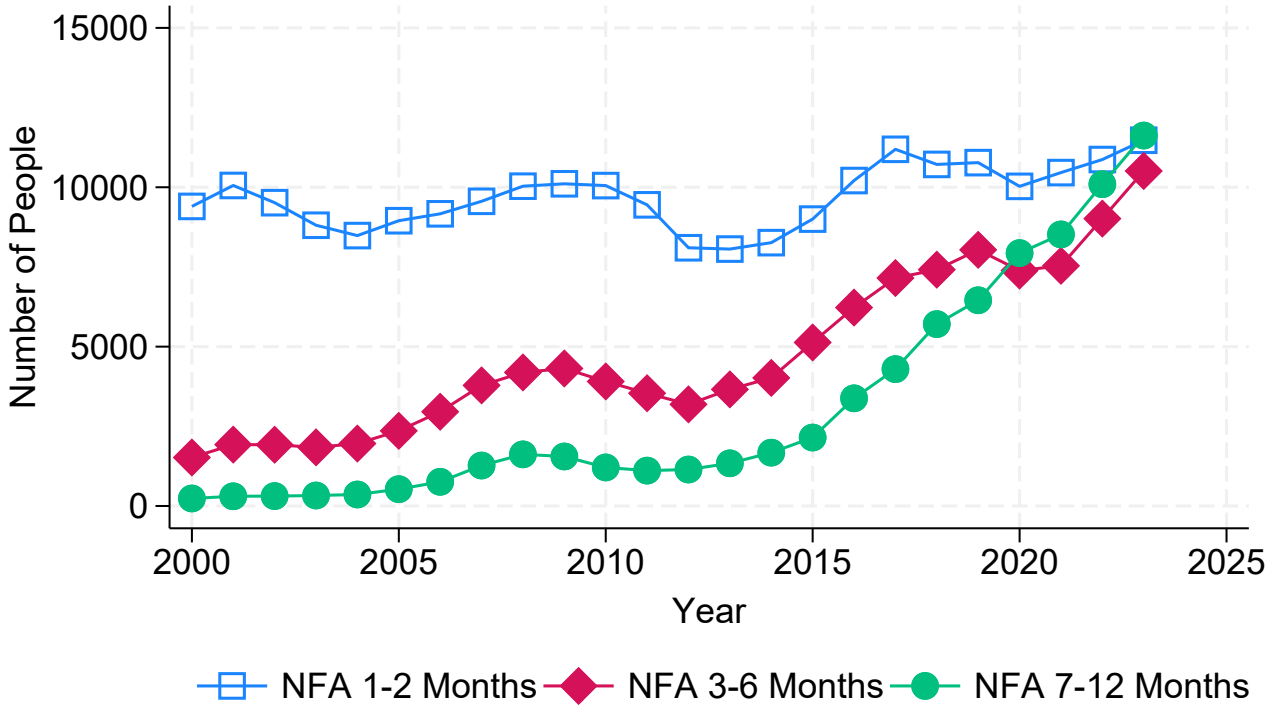
Note: The first bar decomposes the stock of "any homeless" into the proportions accounted for by different homelessness measures: NFA only, NFA and shelter in the same year, shelter only in the year, and persons flagged as homeless in hospital but not NFA or shelter. The second bar shows the fraction 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 B.3: Trends in Homelessness Measured by Point-in-Time Street and Shelter Counts (Indexed to 1 in 2014)



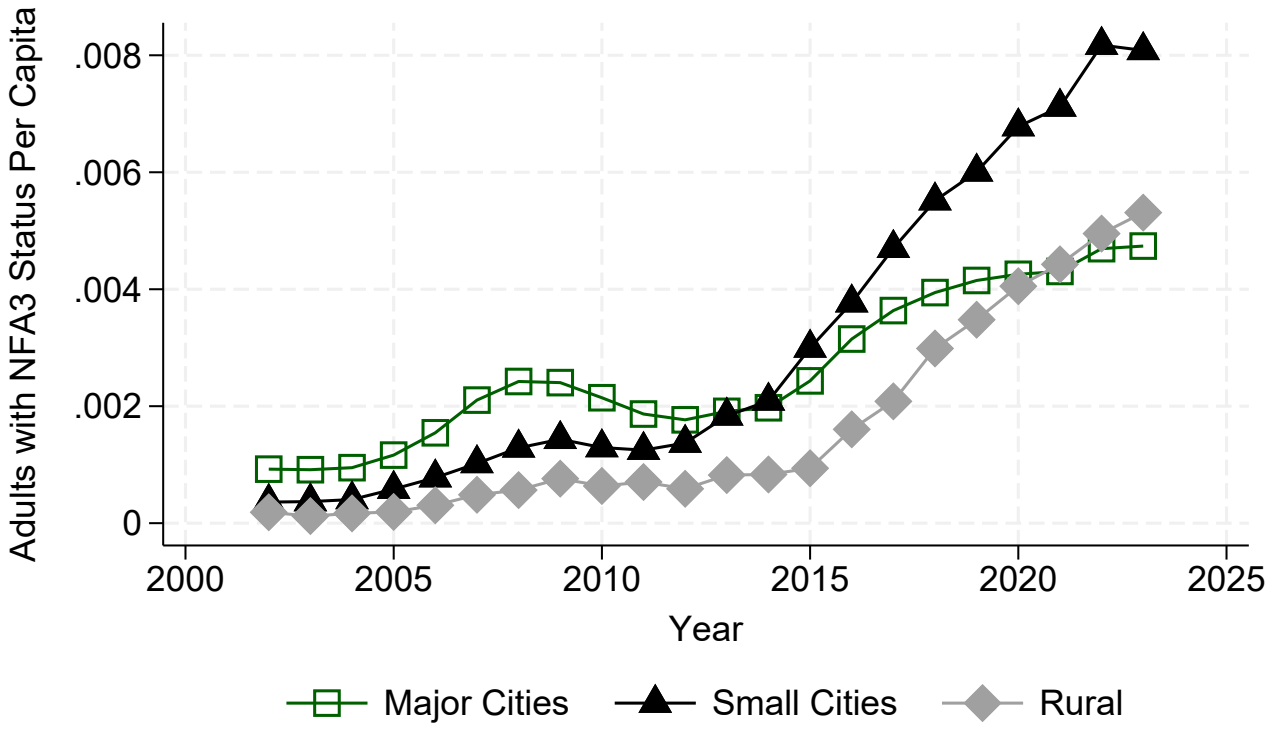
Note: The figure shows trends in the number of people recorded as homeless according to the Point-in-Time Street and Shelter Homeless Counts conducted once per year, for the city of Vancouver and Greater Vancouver respectively. The latter includes neighbouring cities in addition to Vancouver (e.g. Richmond, Burnaby and others). Both series are indexed to 1 in 2014.

Figure B.4: NFA Flagged Persons, by # of NFA Months Received During the Year



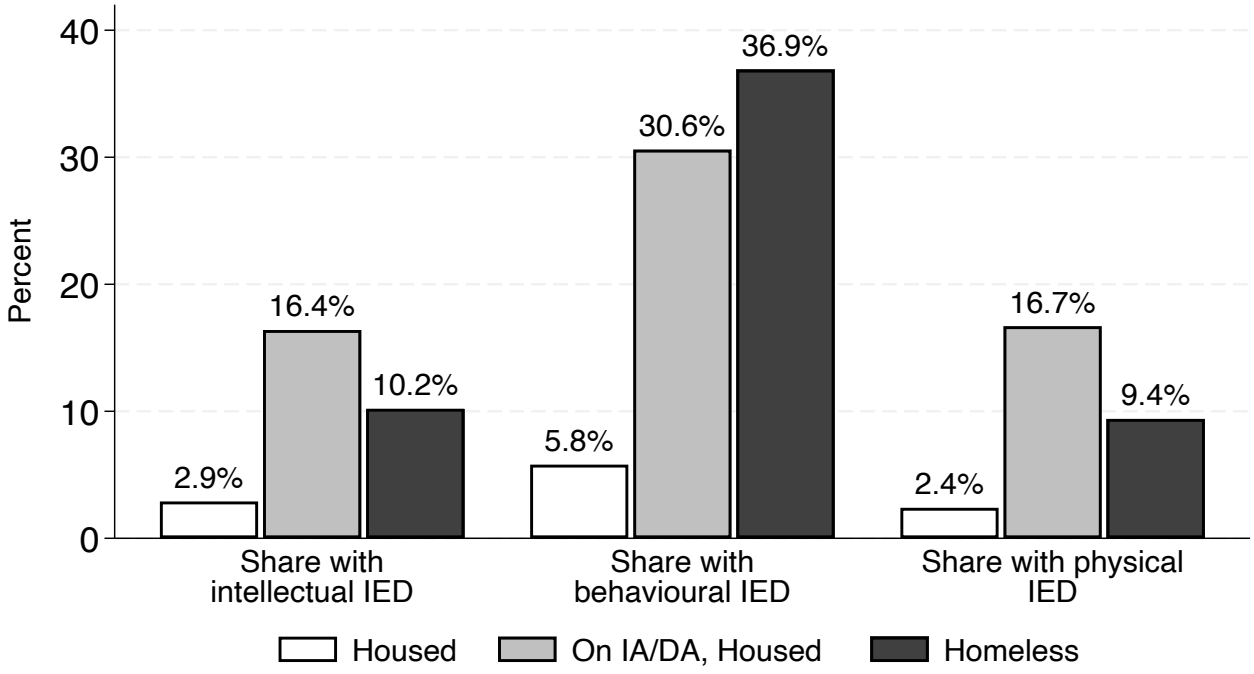
Note: This figure shows the number of unique individuals (of any age) that had no fixed address at any point in a given year, split by the number of NFA months they had within that calendar year.

Figure B.5: Trends in "NFA3" Homelessness Per Capita, by Region



Note: The per-capita rate of NFA3 homelessness among 19-64 year-olds, in each year from 2002-2023, 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 B.6: Inclusive Education Designations in Childhood, by Housing Status



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 the given year (2) never homeless and received IA/DA, and (3) ever homeless in the given year. Variables are conditional on being born in 1986 or later, and on appearing in the BC Ministry of Education enrollment records.

Table B.1: Outcomes Conditional on Entering Homelessness at $s = 0$

Category	Outcome	Likelihood $s = -48$	Likelihood $s = -1$	Bayes Factor $s = -1$
Crime	Discharged From Custody	0.004	0.011	41.0
Crime	In Custody	0.01	0.03	40.5
Crime	Any Criminal Offence	0.01	0.03	40.2
Crime	Community Supervision	0.05	0.08	18.7
Health	Hospital Cost	$127	$810	13.9
Health	ER Cost	$17	$67	9.3
Health	Total Gov Health Cost	$279	$1136	8.3
Health	Number ER Visits	0.06	0.19	8.1
Health	Visited ER	0.04	0.12	6.2
Health	Mental Disorder	0.12	0.23	5.6
Health	Visited Inpatient	0.01	0.05	5.2
Health	Pharmacare Cost	$65	$97	4.7
Health	Head Injury	0.01	0.01	4.6
Health	MSP Costs Excl ER	$70	$162	3.2
Health	Total Pharma Cost	$86	$121	2.4
Health	Received MSP Care	0.3	0.41	1.4
Substance Use	Any SUD Treatment	0.06	0.14	15.8
Substance Use	Received Opioid Agonist	0.04	0.07	14.5
Substance Use	Received AUD Prescription	0.001	0.009	12.2
Substance Use	Days Supplied Opioid Agonist	1.06	1.58	12.1
Substance Use	Days Supplied AUD Prescription	0.02	0.24	10.1
Prescription	Received Antipsychotic	0.07	0.11	6.8
Prescription	Received Gabapentinoid	0.02	0.04	5.8
Prescription	Days Supplied Antipsychotic	3.27	4.66	5.6
Prescription	Days Supplied Gabapentinoid	0.8	1.48	4.4
Prescription	Received Benzodiazepine	0.04	0.04	3.9
Prescription	Days Supplied Benzodiazepine	1.32	1.04	3.6
Prescription	Days Supplied Opioid	1.5	1.23	3.3
Prescription	Received Antidepressant	0.1	0.15	3.0
Prescription	Received Opioid	0.06	0.05	3.0
Prescription	Days Supplied Antidepressant	4.96	6.97	2.1
Family Dissolution	Break Up	0.02	0.03	3.7
Income	Received IA Or DA	0.27	0.41	8.6
Income	Received DA	0.16	0.23	7.0
Income	IA/DA Dollars	$1198	$1312	0.9
Housing	In Supportive Housing	0.004	0.007	3.9

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 3 and 4 report averages, $E[\text{Event}_s|\text{Enter Homelessness}_{s=0}]$. Column 5 reports Bayes Factor, defined as the ratio of the outcome among homeless people with respect to the population that did not enter homelessness ($E[\text{Event}_s|\text{Does Not Enter Homelessness}_{s=0}]$). When the Bayes Factor is 15, that means that homeless entrants' average outcome is 15 times higher than the non-homeless population in event time s.

Table B.2: Cox Proportional Hazard Model

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
A. Demographics			
Male	1.145***	1.125***	1.097***
	[1.092, 1.200]	[1.074, 1.179]	[1.047, 1.150]
Marital status change (base: no change)			
Lost spouse	1.254*	1.249*	1.275**
	[1.051, 1.495]	[1.045, 1.492]	[1.067, 1.524]
Gained spouse	0.770***	0.746***	0.713***
	[0.705, 0.841]	[0.682, 0.816]	[0.650, 0.782]
Family type (base: parent in a couple)			
Single and childless	2.113***	2.081***	2.026***
	[1.904, 2.344]	[1.876, 2.309]	[1.826, 2.248]
Childless couple	1.404***	1.376***	1.338***
	[1.193, 1.651]	[1.169, 1.619]	[1.137, 1.574]
Single parent	1.902***	1.986***	2.094***
	[1.694, 2.135]	[1.769, 2.229]	[1.865, 2.351]
Unknown family type	6.197***	6.449***	6.411***
	[4.441, 8.647]	[4.631, 8.982]	[4.603, 8.928]
B. Criminal Justice Involvement			
Charged with offence	3.001***	2.962***	3.139***
	[2.716, 3.317]	[2.696, 3.255]	[2.863, 3.442]
Prison release	1.815***	1.636***	1.517***
	[1.548, 2.127]	[1.423, 1.880]	[1.346, 1.710]
Remand release	1.619***	1.362***	1.218***
	[1.403, 1.868]	[1.204, 1.541]	[1.091, 1.359]
Community supervision	1.713***	1.510***	1.300***
	[1.571, 1.867]	[1.382, 1.649]	[1.190, 1.419]
C. Health Diagnoses			
Chronic substance use disorder	4.019***	3.297***	2.433***
	[3.782, 4.271]	[3.097, 3.510]	[2.280, 2.595]
Treated for SUD (MSP-billed)	2.726***	2.971***	3.367***
	[2.531, 2.937]	[2.769, 3.189]	[3.138, 3.613]
Chronic mental illness	1.640***	1.586***	1.502***

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
	[1.553, 1.733]	[1.501, 1.675]	[1.422, 1.587]
Schizophrenia	1.510***	1.452***	1.358***
	[1.377, 1.656]	[1.322, 1.595]	[1.231, 1.498]
Other chronic disease	0.977	0.976	0.982
	[0.932, 1.024]	[0.931, 1.023]	[0.935, 1.031]
D. Prescriptions Received			
Alcohol use disorder treatment	1.249*	1.170	1.214*
	[1.018, 1.531]	[0.979, 1.398]	[1.040, 1.417]
Antidepressant	1.146***	1.186***	1.219***
	[1.082, 1.213]	[1.123, 1.253]	[1.154, 1.288]
Antipsychotic	1.313***	1.429***	1.606***
	[1.218, 1.414]	[1.332, 1.534]	[1.503, 1.717]
Benzodiazepine	1.037	1.000	1.017
	[0.951, 1.130]	[0.928, 1.077]	[0.952, 1.087]
Gabapentinoid	1.112	1.126*	1.126*
	[0.977, 1.265]	[1.003, 1.264]	[1.015, 1.250]
Opioid	1.084	1.111**	1.042
	[1.001, 1.175]	[1.039, 1.187]	[0.984, 1.103]
Opioid agonist therapy	0.851**	0.954	1.091
	[0.767, 0.944]	[0.867, 1.050]	[0.997, 1.194]
HCV therapy	0.845	1.287	1.010
	[0.278, 2.568]	[0.609, 2.720]	[0.562, 1.815]
TB treatment	1.844	1.117	1.105
	[0.747, 4.552]	[0.465, 2.683]	[0.549, 2.225]
E. Government Income Support			
Received income assistance (IA)	3.384***	2.801***	2.273***
	[3.159, 3.624]	[2.615, 3.000]	[2.118, 2.439]
Received disability assistance (DA)	2.010***	1.889***	1.788***
	[1.869, 2.161]	[1.760, 2.027]	[1.666, 1.919]
F. Childhood and Family Background			
Foster care (ages 12–17)	1.547***	1.556***	1.554***
	[1.433, 1.669]	[1.441, 1.679]	[1.437, 1.681]

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
Other MCFD involvement (ages 12-17)	1.239***	1.239***	1.231***
	[1.147, 1.337]	[1.145, 1.340]	[1.138, 1.332]
Received IA/DA (ages 12–17)	1.322***	1.335***	1.346***
	[1.254, 1.394]	[1.266, 1.408]	[1.274, 1.422]
Age of mother at birth	0.985***	0.985***	0.986***
	[0.981, 0.989]	[0.981, 0.989]	[0.982, 0.990]
Birth weight (standardized)	0.982	0.981	0.981
	[0.961, 1.004]	[0.958, 1.005]	[0.958, 1.005]
Parents married at birth (base: not)			
Married	0.645***	0.644***	0.643***
	[0.611, 0.680]	[0.610, 0.680]	[0.609, 0.680]
G. Education			
High school graduation (base: did not)			
Graduated (Dogwood diploma)	0.362***	0.353***	0.347***
	[0.341, 0.385]	[0.333, 0.376]	[0.326, 0.369]
Unknown	1.142	1.112	1.067
	[0.882, 1.480]	[0.857, 1.443]	[0.816, 1.396]
Inclusive education designation (base: none)			
Behavioural	1.174***	1.174***	1.174***
	[1.109, 1.242]	[1.109, 1.242]	[1.106, 1.245]
Intellectual	1.131**	1.127**	1.123*
	[1.035, 1.235]	[1.032, 1.231]	[1.024, 1.231]
Physical	1.175***	1.183***	1.188***
	[1.071, 1.288]	[1.079, 1.297]	[1.081, 1.305]
Unknown	0.835	0.825	0.822
	[0.625, 1.116]	[0.616, 1.105]	[0.609, 1.109]
H. Current Neighbourhood Income Decile (base: decile 10)			
Decile 1 (lowest income)	1.684***	1.685***	1.680***
	[1.500, 1.890]	[1.501, 1.892]	[1.497, 1.886]
Decile 2	1.395***	1.406***	1.411***
	[1.240, 1.569]	[1.250, 1.582]	[1.254, 1.587]

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
Decile 3	1.365***	1.370***	1.374***
	[1.211, 1.538]	[1.216, 1.544]	[1.219, 1.549]
Decile 4	1.250***	1.254***	1.259***
	[1.105, 1.414]	[1.108, 1.418]	[1.112, 1.424]
Decile 5	1.244***	1.239***	1.236***
	[1.101, 1.404]	[1.097, 1.399]	[1.095, 1.396]
Decile 6	1.271***	1.273***	1.274***
	[1.124, 1.438]	[1.125, 1.440]	[1.126, 1.441]
Decile 7	1.165*	1.165*	1.158*
	[1.028, 1.321]	[1.028, 1.321]	[1.022, 1.313]
Decile 8	1.140*	1.137	1.133
	[1.004, 1.295]	[1.001, 1.291]	[0.998, 1.287]
Decile 9	1.235**	1.232**	1.224**
	[1.087, 1.403]	[1.085, 1.400]	[1.077, 1.390]
Unknown decile	1.968***	1.935***	1.852***
	[1.481, 2.615]	[1.450, 2.581]	[1.383, 2.479]
Avg. childhood neighbourhood decile	0.979***	0.979***	0.979***
	[0.968, 0.991]	[0.968, 0.991]	[0.968, 0.991]
Unknown childhood neighbourhood	0.718	0.733	0.778
	[0.482, 1.069]	[0.494, 1.090]	[0.524, 1.156]
I. Local Housing Market			
Log median rent (1-bedroom)	0.237***	0.241***	0.252***
	[0.161, 0.350]	[0.163, 0.357]	[0.169, 0.375]
One-bedroom vacancy rate	0.985	0.985	0.986
	[0.970, 1.001]	[0.970, 1.001]	[0.971, 1.002]
J. Census Metropolitan Area Fixed Effects (base: Vancouver, CMA 933)			
Abbotsford–Mission (905)	0.462***	0.468***	0.468***
	[0.334, 0.639]	[0.338, 0.647]	[0.336, 0.650]
Kelowna (907)	0.430***	0.439***	0.457***
	[0.270, 0.686]	[0.276, 0.698]	[0.287, 0.727]
Penticton (910)	0.519	0.540	0.608
	[0.206, 1.308]	[0.217, 1.342]	[0.245, 1.510]
Kamloops (913)	0.548***	0.554***	0.561***

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
	[0.423, 0.709]	[0.428, 0.718]	[0.432, 0.728]
Chilliwack (915)	0.879	0.875	0.866
	[0.763, 1.012]	[0.759, 1.010]	[0.749, 1.001]
Nanaimo (918)	0.499***	0.512***	0.531***
	[0.391, 0.636]	[0.401, 0.654]	[0.414, 0.681]
Victoria (920)	0.405***	0.408***	0.423***
	[0.274, 0.596]	[0.277, 0.600]	[0.288, 0.623]
Prince George (925)	0.692***	0.703***	0.723***
	[0.579, 0.827]	[0.588, 0.841]	[0.603, 0.865]
Terrace (930)	0.574***	0.578***	0.587***
	[0.462, 0.714]	[0.464, 0.719]	[0.470, 0.732]
Cranbrook (932)	0.614***	0.623***	0.638***
	[0.514, 0.734]	[0.520, 0.746]	[0.532, 0.766]
Courtenay (934)	0.838	0.820	0.799
	[0.566, 1.240]	[0.547, 1.227]	[0.529, 1.209]
Squamish (935)	0.719***	0.715***	0.715***
	[0.643, 0.804]	[0.640, 0.800]	[0.638, 0.801]
Whistler (936)	0.620	0.640	0.685
	[0.244, 1.576]	[0.254, 1.613]	[0.272, 1.723]
Campbell River (937)	0.686**	0.691**	0.706**
	[0.538, 0.875]	[0.541, 0.883]	[0.552, 0.904]
Dawson Creek (938)	0.707***	0.717***	0.731***
	[0.590, 0.846]	[0.597, 0.860]	[0.608, 0.879]
Fort St. John (939)	0.512***	0.504***	0.504***
	[0.348, 0.751]	[0.342, 0.743]	[0.340, 0.745]
Nelson (940)	0.491***	0.499***	0.517***
	[0.363, 0.664]	[0.368, 0.678]	[0.380, 0.703]
Quesnel (943)	0.579***	0.576***	0.572***
	[0.446, 0.751]	[0.443, 0.749]	[0.437, 0.748]
Williams Lake (944)	0.751*	0.754*	0.761*
	[0.589, 0.957]	[0.589, 0.965]	[0.593, 0.976]
Kitimat (945)	0.453***	0.466***	0.483***
	[0.311, 0.659]	[0.320, 0.679]	[0.330, 0.707]
Prince Rupert (950)	0.529***	0.533***	0.534***
	[0.388, 0.723]	[0.390, 0.727]	[0.390, 0.732]

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
Trail (952)	0.400***	0.407***	0.424***
	[0.282, 0.567]	[0.285, 0.580]	[0.297, 0.605]
Vernon (955)	0.495***	0.499***	0.503***
	[0.363, 0.674]	[0.366, 0.680]	[0.367, 0.690]
Hope (960)	0.501	0.573	0.678
	[0.052, 4.830]	[0.059, 5.593]	[0.069, 6.629]
Powell River (965)	0.657**	0.663*	0.660*
	[0.483, 0.894]	[0.484, 0.909]	[0.476, 0.915]
Duncan (970)	0.626***	0.638***	0.654***
	[0.500, 0.785]	[0.508, 0.800]	[0.519, 0.824]
Port Alberni (975)	0.647**	0.652*	0.652*
	[0.465, 0.899]	[0.469, 0.906]	[0.468, 0.908]
Salmon Arm (977)	0.657*	0.654*	0.633*
	[0.461, 0.937]	[0.458, 0.934]	[0.442, 0.906]
Rural / No CMA (000)	0.553	0.566	0.612
	[0.245, 1.249]	[0.253, 1.267]	[0.275, 1.364]
CMA unknown (999)	0.605	0.623	0.694
	[0.254, 1.438]	[0.264, 1.469]	[0.293, 1.640]
K. Year Fixed Effects (base: 2005)			
2006	1.377	1.262	1.224
	[0.593, 3.199]	[0.550, 2.898]	[0.534, 2.804]
2007	1.865	1.752	1.631
	[0.827, 4.206]	[0.789, 3.891]	[0.737, 3.607]
2008	2.664*	2.479*	2.316*
	[1.209, 5.870]	[1.143, 5.377]	[1.070, 5.014]
2009	2.625*	2.507*	2.382*
	[1.198, 5.749]	[1.160, 5.416]	[1.105, 5.136]
2010	2.683*	2.547*	2.452*
	[1.230, 5.854]	[1.184, 5.481]	[1.142, 5.267]
2011	2.132	2.018	1.916
	[0.975, 4.660]	[0.936, 4.351]	[0.892, 4.114]
2012	2.173	2.034	1.921
	[0.998, 4.731]	[0.947, 4.368]	[0.896, 4.118]
2013	2.710*	2.560*	2.438*

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Table B.2 — *Continued from previous page*

	(1) 3-Month Lag	(2) 6-Month Lag	(3) 12-Month Lag
	[1.247, 5.889]	[1.194, 5.487]	[1.142, 5.204]
2014	2.992**	2.793**	2.620*
	[1.380, 6.490]	[1.305, 5.974]	[1.227, 5.593]
2015	3.655**	3.435**	3.190**
	[1.688, 7.911]	[1.609, 7.334]	[1.497, 6.798]
2016	4.293***	4.067***	3.869***
	[1.983, 9.293]	[1.905, 8.684]	[1.816, 8.245]
2017	4.674***	4.389***	4.150***
	[2.155, 10.137]	[2.055, 9.370]	[1.947, 8.842]
2018	7.294***	6.835***	6.417***
	[3.363, 15.819]	[3.195, 14.621]	[3.012, 13.675]
2019	7.941***	7.493***	7.008***
	[3.661, 17.222]	[3.503, 16.030]	[3.282, 14.962]
2020	7.752***	7.360***	6.938***
	[3.560, 16.880]	[3.427, 15.806]	[3.243, 14.842]
2021	7.901***	7.471***	7.050***
	[3.629, 17.204]	[3.478, 16.045]	[3.289, 15.111]
2022	8.240***	7.870***	7.471***
	[3.784, 17.942]	[3.664, 16.901]	[3.485, 16.014]
2023	7.493***	7.149***	6.801***
	[3.435, 16.348]	[3.322, 15.384]	[3.173, 14.577]
Model Statistics			
Observations (person-months)	42,723,163	42,723,163	42,723,163
Events (first homeless spells)	9,881	9,881	9,881

Note: This table shows the estimated exponentiated coefficients from equation 1. These 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. 95% confidence intervals in brackets. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.