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SOCIOECONOMIC STATUS AND ACCESS TO MENTAL HEALTH CARE: THE CASE OF PSYCHIATRIC MEDICATIONS FOR CHILDREN IN ONTARIO CANADA

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ABSTRACT

We examine differences in the prescribing of psychiatric medications to low-income and higher-income children in the Canadian province of Ontario using rich administrative data that includes diagnosis codes and physician identifiers. Our most striking finding is that conditional on diagnosis and medical history, low-income children are more likely to be prescribed antipsychotics and benzodiazepines than higher-income children who see the same doctors. These are drugs with potentially dangerous side effects that ideally should be prescribed to children only under narrowly proscribed circumstances. Low-income children are also less likely to be prescribed SSRIs, the first-line treatment for depression and anxiety conditional on diagnosis. Hence, socioeconomic differences in the prescribing of psychotropic medications to children persist even in the context of universal public health insurance and universal drug coverage.

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People of lower socioeconomic status often have unequal access to health care (see for example, Cookson et al. 2016; van Doorslaer, Masseria, and Koolman, 2006; Wagstaff and van Doorslaer, 2000). Low-income individuals tend to be sicker and to consume more care, but holding measures of need constant, people with lower income are often less likely to receive appropriate care (Cutler and Lleras-Muney, 2010). For example, the 2016 U.S. National Healthcare Quality and Disparities Report examines several indicators of the adequacy of care and concludes that poorer people have worse access to care than richer people on most measures. Such disparities have also been found in countries with universal health care, like Canada (Curtis et al., 2001; Curtis and MacMinn, 2008; Allin, 2008).

Disparities in child mental health treatment may be especially concerning given the current crisis in child mental health. In the United States, the American Academy of Pediatrics has joined with the American Academy of Child and Adolescent Psychiatrists and the Children's Hospital Association in 2021 to declare a state of national emergency (AAP, 2021). The Surgeon General also issued an urgent public health advisory about youth mental health (Murthy, 2021). In Canada, Statistics Canada's "Portrait of Youth in Canada," reports that child mental health is worse than it was 20 years ago. They also report that income plays a role in youth mental health: Youth in poor households were less likely to report excellent or good mental health and likelier to report having seriously contemplated suicide.

Child mental health disorders are often more debilitating and harmful for a child's future than common physical health problems. They increase future health care costs and the likelihood of being disabled while decreasing educational attainment and employment prospects (Currie et al., 2010, Smith and Smith, 2010, Goodman et al., 2011).[1] While early treatment offers the promise of improving

[1] Currie et al. (2010) find that children with ADHD and conduct disorders in childhood are more likely (30–100% more likely depending on the child's age) to be on welfare after age 18. Smith and Smith (2010) adults who suffered from mental health problems before the age of 16 have family incomes 20% less than their siblings, with a lifetime difference of $300,000. Goodman et al. (2011) find that children with psychological problems in childhood had 28 percent lower family incomes by age 50.

children's outcomes, some mental health prescribing to children appears to be of questionable appropriateness (Currie and MacLeod, 2020; Cuddy and Currie, 2021, 2022). Moreover, it is possible that poorer children are more likely to be treated in ways that raise questions about appropriateness when they have access to care. Since mental health in childhood is predictive of adult outcomes, such disparities could ultimately contribute to the perpetuation of economic and social inequality (Currie, 2021).

We examine disparities in the pharmaceutical treatment of mental health problems among children in the province of Ontario, Canada. We take advantage of detailed administrative data that tracks children's health care utilization. All Canadians are covered by universal public health insurance programs administered by provincial governments. These programs cover most inpatient and outpatient medical care. But coverage of prescription medications is not universal. In Ontario before January 1, 2018, only low-income children had free public medication coverage. But between January 1, 2018, and March 31, 2019, Ontario provided free universal prescription medication coverage to all children (no premiums, no deductibles, and no copayments). For the first time, millions of children were eligible for free prescription medications. No active "take up" of the program was necessary; pharmacies were responsible for billing the government. However, after a new provincial government gained power, this program was cut back: After April 30, 2019, only children without private prescription medication coverage (offered by parent's employers) were covered by the government prescription drug plan.

We use these changes not to evaluate the effects of the universal public drug coverage program but to identify three groups of children: Low-income children who had medication coverage prior to the change; Children who might otherwise have private medication coverage but who also had public drug coverage between Jan. 1, 2018-March 31, 2019; and children who gained coverage after Jan. 1, 2018 and kept it, indicating that they did not have private medication coverage but had incomes above the low-income cut offs. On average these groups can be thought of as corresponding to low, high, and medium-income families, respectively.

Using these three groups of children we focus on the period of universal drug coverage and show that compared to higher-income children, low-income children are more likely to be prescribed medication “off label,” that is, in a way that is not approved by the U.S. Food and Drug Administration or Health Canada for the diagnoses the children have. Conditional on diagnosis, low-income children are more likely to be prescribed antipsychotics, benzodiazepines, and ADHD (Attention Deficit Hyperactivity Disorder) medications. Low-income children are also more likely to be prescribed, two, three, or four plus mental health medications within a single month (a measure of “polypharmacy”) compared to higher-income children. Low-income children are less likely to be prescribed SSRIs (selective serotonin reuptake inhibiters), the recommended first-line therapy for depression and anxiety, and more likely to be prescribed other types of antidepressants that are not usually recommended for children.

In addition to documenting these disparities in mental health treatment, we investigate the sources of these disparities. We show that while there are differences in treatment across small areas, much of the variation in the treatment of low-income children is within small geographic areas suggesting that it cannot be explained by differences in the supply of different types of providers at the local level. Only a fraction of the difference is explained by children’s prior medical histories and diagnoses. Even conditional on these factors, large differences in treatment within areas remain.

Differences in treatment persist when physician fixed effects are included in the model. This finding indicates that the same physicians are treating children with the same diagnoses and medical histories differently when they are from lower-income and higher-income families. There are similar differences when the sample is restricted to doctors who see all three types of children; when high and low-income children are matched on diagnoses, age, local area, and physician; when children with the highest and lowest medical expenditures over the past year are dropped; and when the sample is restricted so that all of the children are observed for the same length of time and have at least two prescriptions. These findings suggest that there are large socioeconomic differences in prescribing to children with the same diagnoses even with universal drug coverage.

The strength of our research setting is that we can classify individuals by income even without formal income linkages and we can study differential treatment of patients with identical diagnoses, medical histories, and health care coverage. Such an analysis would be extremely difficult to do in a U.S. setting, where high and low-income individuals seldom have the same insurance coverage, and it can be difficult to link prescription records to comprehensive medical records. While it would be possible to conduct this type of analysis in European settings, rates of psychiatric drug use tend to be lower in European children, and prescription guidelines are more proscriptive. Hence, there may be less scope for variation in individual doctor's practice styles in these settings.

The rest of our paper proceeds as follows: Section II distills some of the most relevant background information from the vast literatures on the prescribing of psychotropic medications for children and on socioeconomic disparities in health care. Section III describes the unique setting for our study and the data. Section IV describes the methods we use to analyze the sources of the disparities in treatment, while Section V presents estimation results. Section VI provides a discussion highlighting possible reasons for the disparities in care.

II. Background

This study focuses specifically on the prescribing of psychotropic medications for children and adolescents. The literature identifies several areas of concern. First, antipsychotics are not recommended or approved for use in children except for diagnoses of psychosis and severe conduct disorders, and their use even for childhood conduct disorders is controversial (Pathak et al., 2010, Loy et al., 2017). Yet, in the U.S., most antipsychotics prescribed to children are for ADHD, depression, and anxiety even though there is little evidence that they are effective (Crystal et al., 2009). Potential side effects range from significant weight gain and metabolic syndrome to neurological issues (Daviss et al., 2016; Bushnell et al., 2021; Stroup and Gray, 2018) and the long-term impacts of use in children is unknown. In the U.S., children in foster care and publicly insured children, are the most likely to receive antipsychotics (Crystal et al., 2016).

It is also concerning that so many children receive benzodiazepine prescriptions since they are only approved for the treatment of epilepsy and seizures in children (Bushnell, 2019).[2] In adults, benzodiazepines are mainly prescribed to treat anxiety and have been shown to be effective, although there is a risk of dependency, overdose, and injury (Bushnell, 2019). Benzodiazepines have not been shown to be more effective than placebo in children and these drugs pose a risk of dependency, overdose, and injury (Bushnell, 2019; Ipser et al., 2010; Kuang et al., 2017; Wang et al., 2017).[3]

A third area of concern has to do with the prescribing of antidepressants. Professional guidelines identify Selective Serotonin Reuptake Inhibitors (SSRIs) as the first-line drugs that should be used to treat child and adolescent depression and anxiety if drugs are prescribed at all (Walter et al., 2020, American Academy of Pediatrics, 2018). However, “black box” warning labels are required for most antidepressants including SSRIs because they may increase the risk of suicide in children and young adults. Atypical antidepressants such as monoamine oxidase inhibitors and tricyclic antidepressants can have more serious side effects. Low-income children are more commonly diagnosed with depression than in other children in Canada (Lemstra et al., 2008).

[2] We have dropped the 2,576 children with epilepsy from our sample. A second reason for dropping children with epilepsy is that epileptic children may need to take anticonvulsants which are also sometimes used as mood stabilizers making it difficult to distinguish children being treated for mental health problems.

[3] Since a very short course of benzodiazepines is sometimes prescribed prior to surgery, we also repeat our analysis looking at repeated prescriptions of benzodiazepines within a 30-day period, in order to exclude that type of usage.

ADHD medications for children are also controversial because, while they control some symptoms effectively, medication alone has shown limited ability to improve children's longer-term outcomes (Swanson et al., 2017). ADHD is more commonly diagnosed in children from poorer families and it may be more prevalent in these families due to factors such as a higher incidence of low birth weight and lead poisoning (Russell et al. 2016). However, it is not known how the prescribing of ADHD medications varies by the child's socioeconomic status conditional on diagnosis.

A fifth concern focuses the practice of prescribing multiple psychiatric medications at the same time since "polypharmacy" increases the risk of drug interactions. Zito et al. (2021) argue that polypharmacy may reflect "invalid assumptions about the efficacy of combinations… limited professional awareness of metabolic and neurological adverse drug events, and … infrequent use of appropriate deprescribing." In the U.S., children in the most disadvantaged group are 2.7 times more likely to use three or more psychiatric drugs than children from the most advantaged group (dosReis et al., 2020).

It is difficult to unpack the reasons why socioeconomic status is related to patterns of psychotropic medication prescribing in the U.S. context. Low-income U.S. children are more likely to have Medicaid rather than private health insurance, often face inferior access to health services, and generally see different providers than privately insured children. And since difficult life circumstances are associated with higher rates of mental illness, low-income children may have higher underlying rates of mental health conditions. In the Canadian context, access to services is significantly more equal than in the U.S.: Children all have public health insurance, and they also have universal prescription drug insurance for the period we focus on. Given rich administrative data that identifies locations, diagnoses, and providers, we can compare children with the same diagnosis and who see the same providers. Hence, we ask to what extent differences in utilization by socioeconomic status remain once differences in insurance coverage, residential location, diagnoses, and providers are accounted for.

b) Disparities in health care by socioeconomic status

While there is little dispute about the existence of disparities, it is more difficult to document their causes. There are several demand-side reasons why poor people receive less care or lower quality care than richer people with a similar health status. Most obviously, low-income individuals may be financially constrained, especially if they lack adequate health insurance. Allin and Hurley (2009) show that in Canada, patients who lack prescription medication coverage are less likely to see a doctor even though the doctor visit itself is covered by public health insurance. The poor may also find it more costly to seek care due to inflexible work schedules or transportation costs (Acton, 1975; Smith et al. 2022). Low-income individuals may also have different time preferences or attitudes towards risk compared to others (Fuchs, 1982). Or they may simply have worse information about the benefits of medical care (Lleras-Muney and Glied, 2008). Some low-income individuals may distrust medical authorities and be correspondingly slower to seek care and less likely to follow up on provider recommendations (Alsan and Wannamaker, 2018; Alsan et al., 2019).

Despite the literature's emphasis on demand-side factors, there is increasing evidence that supply-side factors are important drivers of disparities in treatment (Chandra and Skinner, 2004). Cutler et al. (2019) document large differences in doctors' beliefs about appropriate treatment. Finkelstein et al. (2015) look at elderly movers and suggest that at least half of the observed variation in procedure use is due to supply-side rather than demand-side factors. Deryugina and Molitor (2020) show that elderly New Orleans residents displaced by Hurricane Katrina lived longer if they were evacuated to places with healthier populations. Hence, to the extent that poor people are concentrated in areas with worse health care access, or lower quality care, this could account for some of the observed disparities.

The idea that disparities in treatment are driven largely by characteristics of local areas, and especially by shortages of qualified health professionals, is prominent in discussions of child mental health treatment. Findling and Stepanova (2018) and McBain et al. (2019) highlight shortages of child psychiatrists in the United States. Fremont et al. (2008) conclude that such shortages force doctors in family medicine to treat children with mental health problems, even when they are not comfortable doing so. However, Cuddy and Currie (2020) report that differences in the supply of providers account for only a small share of the observed differences in treatment and that there are wide variations in the care delivered by practitioners within small areas.

A third explanation for health care disparities is that the same providers provide different treatment to poor patients, even in settings where all patients have the same health insurance. Brekke et al. (2018) study diabetic patients in Norway and find that doctors provide fewer services to less educated and lower income patients even though all services are covered by public health insurance. Several studies focus on hospital waiting times in public hospitals and find that conditional on clinical factors, patients of higher socioeconomic status had systematically lower waiting times (Meliyanni et al., 2013, Moscelli et al., 2018). Hajizedeh (2018) finds that the poor also wait longer for appointments in Canada.[4]

Our work is informed by this prior literature. We show that in the case of psychotropic medications, there are large within-area differences in the treatment of children by socioeconomic status. These within-area differences persist when we control for detailed patient characteristics, medical histories, and diagnoses. Most tellingly, they persist when we examine patients who see the same providers during the same universal prescription coverage period. These findings suggest that

[4] Angerer et al. (2019) conduct a clever audit study in Austria in which mock patients sent emails seeking to book doctor's appointments. The authors found that physicians responded more quickly, and offered lower wait times, when the patients signaled (via their titles) that they possessed an advanced degree.

interactions between individual providers and their patients are an important source of socioeconomic disparities in care within areas with similar service provision. We also show that there are large differences in the treatment of children between high and low-income areas, which may be consistent with differences in the availability of services.

III. Data and Institutional Setting

Ontario has universal public health insurance for medical care under the Ontario Health Insurance Program (OHIP). However, public coverage of prescription medications is handled via the separate Ontario Drug Benefit (ODB) program. We take advantage of rich administrative data from OHIP and ODB as well as sweeping changes in the ODB program to analyze mental health prescribing for children and youth in Ontario between 2016 and 2019. Children and youth are defined as those who were less than 20 years of age when we first observed a prescription for a mental health medication. The OHIP and ODP datasets were linked using unique encoded identifiers and analyzed at ICES.[5]

a) Prescription Drug Coverage Under the ODB Program

Public coverage of prescription medications for children under ODB changed dramatically in 2018 and we use these changes to identify children from low-income families as described in this section.

Before January 2018, most children on ODB lived in households eligible for financial support under the Ontario Works Program or the Ontario Disability Support Program. In 2022 the income cutoffs for Ontario Works were $10,000 (Canadian Dollars) for a single person, $15,000 for a couple,

[5] ICES is an independent, non-profit research institute whose legal status under Ontario's health information privacy law allows it to collect and analyze health care and demographic data, without consent, for health system evaluation and improvement. The use of the data in this project is authorized under section 45 of Ontario's Personal Health Information Protection Act (PHIPA) and does not require review by a Research Ethics Board.

plus $500 for each dependent.[6] Hence, only very low-income households were eligible for this benefit. The Ontario Disability Support Program provides income support for individuals with a severe and prolonged impairment; a family with two adults and a child under 17 would be eligible for a basic needs allowance of up to $1,341 and a maximum shelter benefit of $846 per month.[7] These rules indicate that only low-income households were eligible for this benefit, similar to Medicaid coverage in the United States. Approximately 3.8% and 4.2% of the entire under-65 population of Ontario were on Ontario Works or the Ontario Disability Support Program in fiscal year 2018 (Maytree 2022).

In January 2018, the government suddenly announced that all Ontarians under age 25 would receive free coverage of any medications in the ODB formulary under a rebranded plan called OHIP+. Take-up was not an issue with OHIP+ because it was not necessary for people to enroll—all children were eligible and pharmacists billed the government directly.[8] The number of children with public medication coverage skyrocketed almost ten-fold from 168,126 in fiscal year 2016-2017 to 1,512,433 in fiscal year 2018-2019, out of an estimated three million Ontario children (Ontario Ministry of Health, 2022). These latter numbers suggest that over the course of a year, and with full medication coverage, about half of Ontario children would need to have a prescription filled. However, April 2019 saw retrenchment (following the election of a new conservative provincial government) and children with private medication coverage became ineligible for OHIP+. The number of children utilizing the program subsequently fell to 608,653 in fiscal year 2019-2020 (Ontario Ministry of Health, 2022).[9]

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[6] Ontario Works also has asset limits ($10,000 for a single person) which excludes the primary residence, one vehicle, and any education or disability savings plans. See https://www.ontario.ca/page/eligibility-ontario-works-financial-assistance for information about Ontario Works.

[7] See https://www.ontario.ca/document/ontario-disability-support-program-policy-directives-income-support/61-basic-needs for information about the Ontario Disability Support Program.

[8] The only exception is that some children may have taken medications that were not in the formulary, but were covered by private health insurance. The ODB program is considered to be one of the most generous drug benefit programs in Canada. It covers more than 5,000 drugs, and drugs not listed in the Formulary are still eligible for coverage, on a case-by-case basis, through the Ministry of Health's Exceptional Access Program (EAP). See https://www.health.gov.on.ca/en/pro/programs/drugs/formulary43/edition_43.pdf for further information.

[9] The main reason people didn't drop their private medication coverage is likely that parents needed their own medication coverage. If they opted for adult coverage from private plans offered through their employers, then children could also be covered under those plans for little to no additional cost.

Figure 1 shows the number of mental health prescriptions and the number of children receiving a mental health prescription paid for by the Ontario Drug Benefit over the sample period. One can clearly see the huge increase in the number of ODB prescriptions and children served during the initial OHIP+ period and the retrenchment after April 2019.

Evidently, the average characteristics of the children covered are quite different in each phase of the plan. Before OHIP+, only children in low-income households were covered. Once all children became covered, the sample became more representative of all children in the province. However, in the last eight months of the data, the sample includes only children without private medication coverage, which means that they are likely to be drawn from the medium and lower parts of the income distribution (Barnes and Anderson, 2015).

We take advantage of these policy changes to "tag" children by socioeconomic status. That is, if children were covered prior to January 2018, we know they are low-income and tag them as such throughout the sample. On average and controlling for age, children who only appear in the sample after January 2018, but disappear again after April 2019 are likely to have access to private drug coverage through their parent's employers, and hence are likely to be relatively high-income (Barnes and Anderson, 2015). Children who first appear in the ODB records after January 2018 and remain in the sample after April 2019 are more likely to include those whose household income was too high to qualify for pre-OHIP+ coverage, but who do not have access to private medication coverage which is more prevalent for workers in higher paying jobs. In what follows, we tag these three groups as low-, high-, and medium-income respectively.

Clearly this tagging process is complicated by children's age. By construction, children who first appear in the pre-OHIP+ period are not only poorer but have had more time to be diagnosed and treated with a mental health condition. Hence, in all our analyses, we control for single year of age so that comparisons always involve children of similar age.

However, even conditional on age, there will be some unavoidable measurement error in tagging. For example, there will be some low-income children who first appear in the prescription drug data during the OHIP+ expansion period (and thus get incorrectly classified as "high income") because they did not previously fill prescriptions. Hence, while those we tag as low-income are accurately identified, those we tag as relatively high-income are so only on average. This measurement error means that the low/high-income contrasts we identify are likely to be understated relative to the true income gradients in treatment because the "high" group contains some low-income individuals. These considerations suggest that the effects we find should be interpreted as lower bounds on true disparities in treatment.

In what follows we consider alternative comparisons in which each income group has the same number of prescriptions over exactly the same time intervals. We also estimate models in which we drop the children with the highest and lowest overall medical expenses, in order to make the two groups as similar as possible. Finally, we conduct matching exercises in which low income and high-income children with the same age, diagnoses, locations, and providers are matched. All of these alternative specifications yield very similar estimates.

Our focus is on differences in the types of mental health medications prescribed to children in the three groups. Just prior to the OHIP+ expansion in fiscal year 2016-2017, 40,041 children, comprising 24% of all children who used public coverage for any prescriptions, filled at least one mental health prescription using the public plan. These children represented approximately 1.3% of all Ontario children. During the expansion period, in fiscal year 2018-2019, 244,462 children comprising approximately 16% of all child ODB patients filled at least one ODB mental health prescription. These children represented about 7.9% of all Ontario children, suggesting that the use of at least one mental health medication is widespread among Ontario children.

The mental health prescriptions we observe fall into seven broad medication classes: Attention Deficit-Hyperactivity Disorder (ADHD) medications, antipsychotics, selective serotonin reuptake inhibitors (SSRIs), other antidepressants (including tricyclic antidepressants, monoamine oxidase inhibitors, and serotonin norepinephrine reuptake inhibitors (SNRIs)), benzodiazepines, and mood stabilizers and anticonvulsants. The list of specific medications that fall into each medication class can be found in the Appendix.

The main data set includes 3,530,010 million mental health prescriptions filled by 237,835 youth from January 1, 2016, to December 31, 2019 and paid for by the ODB program. We observe the date the prescription was written and a prescriber identifier.[10] In addition, we have prescription and medical data starting in January 2010 for every child who received a mental health prescription.

Table 1 provides an overview of prescription patterns, medical histories, and background characteristics for the three groups of children. Because children may be observed for varying lengths of time, the unit of analysis in this table is the patient-year. Table 1 suggests that there are large differences in mental health prescribing patterns by income. Low-income children with any mental health prescriptions have 13.74 mental health prescriptions per patient-year compared to 5.19 prescriptions per patient-year in the higher income, privately insured group. The "gained coverage" group is in between with 10.86 prescriptions per patient-year. Most of these prescriptions are for 30 days.

Much of this difference in the number of prescriptions is due to low-income children's higher probability of being prescribed two or more different psychiatric medications in the same month (a measure of polypharmacy). For example, in a typical patient-year, 50.6 percent of low-income children

[10] Between January 2016 and December 2019, we observe 23,168 physicians prescribing mental health prescriptions to an average of 25.2 unique child-years.

receive two or more medications and 8.8 percent receive four or more medications compared to rates among privately insured children of only 34.3 percent and 3.1 percent, respectively.

Turning to specific psychiatric medications, one can see that in any given patient-year, 58.9 percent of low-income children who filled a prescription for any mental health medication got a prescription for an ADHD medication compared to 50.0 percent of privately insured children. The differences are greater for other types of medication: 29.0 percent of low-income sample children received an antipsychotic in each patient year compared to only 11.2 percent of privately insured children. Low-income children are also more likely to receive benzodiazepines and mood stabilizers (9.1 and 9.3 percent respectively) than privately insured children (6.5 and 4.7 percent respectively). Turning to antidepressants, low-income children are less likely to be prescribed SSRIs (32.4 percent) compared to the privately insured (43.1 percent) but are more likely to be prescribed other antidepressants (11.4 percent vs. 4.7 percent for privately insured children).

An important question for our analysis is whether low-income children are "sicker" in a way that justifies the different patterns of medication use. In addition to the ODB data on mental health drugs, we also have encounter-level data from the main OHIP administrative files which include information about emergency department visits, inpatient hospitalizations, mental health outpatient visits, and total cost of medical care for all youth who ever appear in the mental health prescription sample. The sample was drawn so that there is at least a 12-month look back period prior to the first observed mental health prescription.[11] Dates and lists of diagnosis codes are available for each encounter. The cost data captures actual tax-payer costs. Costs are summed across all medical encounters and prescriptions within a 365-day period relative to each child's first prescription date.

[11] We have data to the end of 2020 but given all the disruptions in care that occurred in 2020, we have only used this data to identify a small number of children with epilepsy so that they can be omitted from the sample. .

The fourth panel of Table 1 examines these measures of medical history with a view to quantifying differences between low-income and other children. The table shows that most patient-years in the sample include an outpatient mental health visit. The rates are similar for low-income children and for the privately insured (71.4% vs. 66.8%), but significantly higher for the medium-income group (82.7%).

In this population of children using mental health medications, trips to the emergency department (ED) and hospitalizations for any cause are relatively frequent, with 10.4 percent of low-income children, 7.8 percent of children with private prescription drug coverage, and 13.1 percent of those who gained coverage (middle income) using an ED with a mental health indication in a given year. Overall, spending for the low-income children is higher at $1,200 (2019 dollars) per patient-year compared to $778 for the privately insured and $921 for the group that gained and kept coverage.

These figures suggest that low-income children are able to access public mental health services at a rate comparable to other children. Low-income children do have slightly higher usage of outpatient mental health services as well as higher rates of ED use and inpatient hospitalization compared to children with private prescription drug coverage, which might be because they are sicker but could also be due to the side effects of inappropriate treatment, or to a lack of other types of social supports that necessitate hospital use.

In what follows, we address the possibility that low-income kids could be sicker by controlling for diagnosis codes as well as medical history. Specifically, we control for a vector of nine indicators for whether a child has ever been diagnosed with one of the following conditions: psychosis, anxiety, depression, bipolar/mania, conduct disorder, ADHD, developmental disorder, intellectual disorder, and substance use disorder. It is possible for a child to have multiple diagnoses. We also include indicators for hospitalization for any reason, hospitalization for mental health, hospitalization for injuries, emergency department visit for any reason, emergency department visits for mental health, emergency department visits for injuries, and an indicator for use of any outpatient mental health services over the past year. We also include controls for the same set of variables computed in the 30 days prior to a prescription. As a robustness check we also estimate models excluding the top and bottom 5% of children by total health care expenditures in order to make the samples more comparable.

As discussed above, some of the prescribing behaviors we document, such as prescribing antipsychotics for children without psychosis, repeatedly prescribing benzodiazepines, or prescribing three or four psychiatric drugs at once, are hard to justify even for very sick children. And it is difficult to understand why low-income children would receive other antidepressants instead of SSRIs, which are generally recommended as the first line treatment for children with depression. In what follows, these questionable practices are all shown to be more likely for low-income children conditional on diagnosis.

The last panel of Table 1 provides some validation of the tagging procedure used to identify the low-income children. It shows that children tagged as "low income" are much less likely to be living in high income, urban postal areas (FSAs).[12] The next two rows suggest that some of the differences in prescription patterns could reflect differences in the demographic characteristics of children in different groups. Although by construction children in the low-income group have been in the sample more years, we find that children in the group with private drug coverage are about a year older on average than children in the other two groups. They are also more likely to be female. These demographic differences will be controlled for in the estimation described below. In addition, we show estimates using data matched on demographics as well as FSA and diagnosis.

b) <u>The Relationship Between Use of Psychiatric Drugs and Use of Other Mental Health Services</u>

[12] An FSA is like an American zip code and is indicated by the first three digits of the postal code. As an example, there are 96 FSAs within the city of Toronto and 179 within its census metropolitan area. There are 513 FSAs in Ontario.

For the universal coverage period (January 1, 2018—March 31, 2019) we observe all prescriptions for psychiatric medications (from ODB) as well as all of the medical records (from OHIP). Hence, we can use the data for this period to try to understand the relationship between receiving mental health drugs and receiving other publicly-funded mental health services. This relationship is illustrated in Figure 2. About 36.6% of all children receiving public mental health treatments other than medication also received a prescription for a psychotropic drug. However, of children receiving a prescription, the vast majority, 86% also received other mental health treatments that are observable in the OHIP data. Only 28,994, or only approximately 14% of children who received a mental health prescription, did not receive any other type of publicly paid for mental health treatment. This means that we have diagnostic information from encounters with the public system, as well as from the prescription data for most of our sample.

c) Area-level data

We also use data from the universal coverage period (January 1, 2018—March 31, 2019) to construct an area-level data set based on all publicly-funded encounters for covered mental health care. We use this secondary data set to examine variations in mental health care across high and low-income FSAs, as well as by smaller "dissemination areas" within FSAs. In order to identify high-income FSAs, we merged in average income for each FSA from Revenue Canada's tables on individual tax returns in 2018. The bottom quintile cutoff is $42,286 and top quintile is $63,095 in 2018 dollars.

The average Ontario FSA had 25,714 people in 2016 which is quite large. FSAs are divided into smaller dissemination areas (DAs) which each have 400 to 700 people. This is the smallest standard geographic area used by Statistics Canada. In addition to knowing the FSA, we know whether the DA is rural and its income quintile *within* the FSA. This gives us two possible proxies for area-level income measures, one at the FSA-level, and a finer DA-level measure within the FSA that allows us to distinguish relatively high and low-income areas within an FSA.

IV. Methods

As discussed above, the main sample of children includes all those who received mental health prescriptions covered by ODB at any time between Jan. 1, 2016 and Dec. 31, 2019. Our baseline specification estimates patient-year-level regressions using data on all of these children during the period of universal access from Jan. 1, 2018 through March 31, 2019. We estimate a series of models adding one set of control variables at a time. The most fully specified models takes the form:

$$(1)\quad \text{OUTCOME}_{ift} = \beta_1\text{LOWINC}_{ift} + \beta_2\text{AGE}_{it} + \beta_3\text{MALE}_i + \beta_4\text{MEDHIST}_{it} + \beta_5\text{DIAGNOSIS}_{it} + \beta_6\text{FSA}_f + \beta_7\text{DOCTOR}_{ift} + \varepsilon_{ift},$$

where the subscripts indicate child *i* in FSA *f* at time *t*; the outcomes are the type of medication prescribed; LOWINC indicates that the child is tagged as low-income; AGE is a vector of single year of age dummies; and MALE is a dummy variable for gender. The vector MEDHIST includes indicators for whether the child visited the ED for any reason; whether they visited the ED for a mental health reason; whether they visited the ED for an injury; whether the child was hospitalized for any reason; whether the child was hospitalized with a mental health diagnosis; whether the child was hospitalized with an injury; and whether the child had an outpatient visit with a mental health code. These variables are all measured over both the past 30 days, and also over the past year. We also include the log of the prior year's total medical costs (plus $1) measured in 2019 dollars. DIAGNOSIS is a vector of nine indicators for whether they have ever been diagnosed with psychosis, anxiety, depression, bipolar/mania, conduct disorder, ADHD, developmental disorder, intellectual disorder, and substance use disorder, as well as fixed effects for the two most recent mental health diagnosis codes. Equation (1) also includes an FSA fixed effect which controls for the geographic availability of care at the local level.

An exciting feature of our data is that it includes an (anonymized) provider ID so that it is possible to include provider fixed effects. This inclusion allows us to determine whether providers are treating high- and low- income patients who live in the same FSA and have similar medical histories differently in terms of the prescription of mental health medications. Robust standard errors are clustered at the FSA-level in order to allow for correlations in treatment within FSA (e.g., due to the availability of services).

a) Exploring Robustness

Equation (1) is also estimated using a broader period that includes data from January 1, 2016 to March 31, 2019. This broader time interval increases the sample size from 206,425 to 230,683 children. A possible critique of this specification is that low-income children may be observed from January 2016 through March 2019 but high-income children can only be observed from January 2018 through March 2019. Thus, low-income children could be observed at a later stage of their mental health treatment.

In a second set of robustness exercises we address this critique by following each group for exactly 15 months (the length of the expansion period). We also add an indicator for the middle-income "gained coverage" group in addition to the one for low-income children. Further, because we identify those who gained coverage as individuals who received a prescription both during the expansion period and after the expansion ended (i.e., at least two prescriptions over a given time frame), in this analysis *all* are required children to have at least two prescriptions over 15 months. Specifically, a low-income child must have received at least two prescriptions between October 1, 2016 and December 31, 2017; a privately-insured child must have received at least two prescriptions during the expansion period; and a child who gained coverage must have received a prescription between October 1, 2018 and March 31, 2019, as well as at least one prescription in the post-expansion period up to December 31, 2019. These restrictions reduce the sample size to 171,406 children.

An additional potential concern is that even low-income children with private drug coverage who live in the same FSAs may see different providers with different practice styles. To address this issue, a third robustness exercise restricts the sample to children seen by providers who treat children drawn from all three income groups. This restriction reduces the number of unique prescribers substantially, from 16,495 to 4,526; however, it has a smaller effect on the number of children which falls from 206,425 to 146,697.

In a similar exercise, low-income children are formally matched to children with private drug coverage who have the same demographics, live in the same FSA, and have the same diagnoses. An additional set of matching models matches on the provider as well. These models look at differences in how providers treat low-income children with the same demographics, general address, and diagnoses compared to how they treat children with private drug coverage.

In an additional attempt to make the samples of low-income children and higher-income children as similar as possible, we estimate models excluding the bottom and the top 5% of children by prior year medical expenditures. As shown in Appendix Figure 1, children at the top of the expenditure distribution are more likely to be low-income while children at the bottom of the expenditure distribution are more likely to be high income. Hence, excluding these children makes the two samples more similar in terms of underlying illness distributions.

Finally, we provide some additional evidence that low-income children receive prescriptions that are less medically appropriate. We do this by examining the effect of low-income on the prescribing of antipsychotics to children without diagnoses of psychosis or conduct disorders; by examining repeated prescriptions for benzodiazepines; and by examining the prescription of SSRIs for children with bipolar disorder. This last practice is one that should be avoided because giving SSRIs to people with bipolar disorder can induce mania.

b) <u>Area-level analyses</u>

As discussed above, differences in area-level characteristics including access to care are one of the leading explanations for variations in utilization of care. Hence, we also provide a supplementary analysis of variations in utilization of mental health care across high and low-income Ontario postal areas (FSAs) using area-level data. These descriptive cross-sectional regressions have one observation per FSA and take the form:

(2) $Outcome_f = \beta_1 FSA_f^{top} + \beta_2 FSA_f^{bottom} + \varepsilon_f$,

where $Outcome_f$ is one of several different measures including the share of all Ontario children who received any medical mental health care (i.e., mental health care other than psychiatric prescriptions), the share who received mental health outpatient care, the share receiving mental health care in an emergency department, and the share receiving mental health care in the course of hospitalization. We then examine the share of children who are prescribed a mental health medication conditional on receiving any mental health care.

FSA_f^{top} indicates that the FSA f is in the top quintile of FSAs by income while FSA_f^{bottom} indicates the bottom quintile of FSAs by income. These regressions provide a summary description of how the use of services differs across high- and low-income areas.

A second set of area-level models take the form:

(3) $OUTCOME_d = \alpha_{FSA} + \beta_1 DA_d^{top} + \beta_2 DA_d^{bottom} + \varepsilon_d$.

These models include FSA fixed effects (α_{FSA}) so that they investigate the same set of outcomes for high and low-income areas *within* FSAs. In these models, each FSA has been split into five groups. DA_d^{top} represents the highest income quintile of small areas within the FSA while DA_d^{bottom} represents the lowest income quintile of small areas within the FSA. Importantly, an FSA is small enough in terms of area that people living within an urban FSA have approximately equal geographic access to care.[13] Hence, these models come closer than model (2) to describing how utilization of care varies with income within an FSA. These regressions are weighted by the FSA population aged 0 to 19, and the standard errors are clustered at the FSA-level.

In addition to examining the overall receipt of care during the expansion period, we estimate versions of (2) and (3) in which the outcomes are mental health prescriptions broken down by the type of medication. These models allow us to investigate how the prescription of particular drug classes varies with socioeconomic status.

V. Results

Table 2 presents estimates of equation (1) based on the data on prescriptions at the individual patient-year level. The table focuses on the expansion period of universal drug coverage when all children had equal public drug coverage in addition to public health insurance. Recall that children are tagged as "low-income" if they participated in ODB prior to the expansion. The table presents only the coefficients on "low income" from 30 different regressions—each coefficient is from a separate model.

Dependent variable means are shown in column (1), for the sake of comparison. Column (2) of Table 2 shows a version of equation (1) that includes only the FSA fixed effects and excludes all the other variables. Each subsequent column shows the effect of adding an additional set of variables until the last column, column (6) shows fully specified model including prescriber fixed effects. These models provide a picture that is remarkably consistent across the columns of the table. Within FSA, low-income children are more likely to be prescribed antipsychotics, benzodiazepines, ADHD drugs

[13] As an example, a map of FSA K2E is available here: https://www.zipdatamaps.com/en/canada/ontario/fsa/k2e. Within this area, and according to Google maps, it would take 12 minutes by public transit to get to the Royal Ottawa Psychiatric hospital from the closest point in the FSA compared to 31 minutes from the furthest point. Driving, the comparable times are 6 minutes and 16 minutes. This example pertains to an urban area, so distances would be correspondingly further in rural areas.

and mood stabilizers. They are less likely to be prescribed SSRI and more likely to be prescribed other antidepressants, which generally carry greater side effect risks.

Columns (4) and (5) of Table 2 show that adding controls for medical history and diagnoses has relatively small impact in the models for most of the medications one age and sex are in the model. For example, the coefficient on low income in the model for antipsychotics falls from 0.166 in column (3) to 0.133 in column (5). A comparison of column (5) and column (6) shows the impact of adding prescriber fixed effects. In all cases, the estimates remain statistically significant. For example, the coefficient on low income in the model for antipsychotics falls from 0.133 to 0.122. The stability of these estimates indicates that large within-area differences in the treatment of low-income children remain even after controlling for demographics, medical history, diagnoses, and the child's prescriber. In other words, it appears that the same physicians are treating children with similar medical histories and diagnoses differently, a finding that is probed further below.

Panel B of Table 2 provides a similar set of results for the effect of low income on the probability of polypharmacy, defined as receiving two, three, or four plus psychiatric medications prescribed within the same month. The results indicate that in the fully specified model, low-income children are 29.9% more likely to receive two or more medications, 76.3% more likely to receive three or more medications, and 94.6% more likely to receive four or more psychiatric medications in a single month. These are effect sizes as a percent of the baseline mean.

a) Robustness

Appendix Table A1 replicates Table 2 but adds the controls in a different order. Age and sex are added first, and then the impact of including additional controls, including the FSA fixed effects, can be compared to that baseline regression. The table shows that once age and sex are controlled, medical histories, diagnoses and area fixed effects have relatively little impact. Hence, the estimates are remarkably robust to the inclusion or exclusion of additional controls beyond age and sex.

Appendix Table A2 shows models identical to those in Table 2 but estimated using a smaller sample that drops children with the highest and lowest total medical expenditures in the past year. The idea is to try to make the high income and low-income children as similar as possible. Once again, these estimates are similar to those discussed earlier.

To further assess the robustness of our findings, Table 3 presents a somewhat different comparison that uses all the data from January 2016 to March 2019. As discussed above, the inclusion of the data from 2016 and 2017 increases the sample size. Table 3 compares children who were prescribed psychiatric medications between January 2016 and December 2017, to children who were prescribed medications between January 2018 and March 2019 but who did not receive prescriptions in the earlier period. As discussed above, children covered by ODB prior to Jan. 1, 2018 were low income. Children covered during the expansion but not during the prior period are mostly higher income. Table 3 shows patterns that are very similarly qualitatively, though the estimates are somewhat smaller, especially for ADHD medications. Since the use of ADHD medications is growing over time, the smaller effects of low income when low-income children are measured only in the earlier time period could reflect these trends.

A potential problem with the analysis using the longer time period is that some low-income children have been observed since 2016, so there is a longer window in which they could have been prescribed a psychotropic medication. In contrast, the privately insured children are only observed for 15 months between January 1, 2018 and March 31, 2019. Moreover, to date, we have said nothing about the middle group, those who were able to retain ODB coverage for the rest of 2019 because they did not have private drug coverage. Hence, as a second robustness check, we estimate a version of (1) which includes an indicator for “gained coverage.” Each child is followed for 15 months and all children have at least two prescriptions. The reason for the second restriction is that the “gained coverage" group is identified only if they received prescriptions both during the universal coverage period and afterwards. as well as for low-income children.

Estimates from the fully specified model with all covariates including prescriber fixed effects are shown in Table 4. The estimated effects of low income are qualitatively similar to those shown in Column (6) of Tables 2 and 3, though the estimated effect of low income on antipsychotic prescriptions is even larger in this specification.

The estimates for the "gained coverage" (middle-income) group fall between the low-income and the privately insured group in the models for antipsychotics, other antidepressants, benzodiazepines, and mood stabilizers. However, the gained coverage group are slightly more likely to be prescribed SSRIs than privately insured children (about 2%) and are less likely to be prescribed ADHD medications than either the low-income or the privately-insured children.

Table 5 shows models like those in Table 2 but estimated using a smaller sample that includes only children treated by prescribers who saw all three types of children. These estimates are qualitatively similar to those discussed above, with the exception that the models with prescriber fixed effects yield estimates that are uniformly slightly larger than those in Table 2.

Table 6 shows estimates from matching models in which low-income children are matched to other children. Two versions of the model are shown. In the first column, low-income children are matched to other children of the same sex, FSA, age group (0-1, 2-4, 5-9, 10-13, 14+), and vector of diagnoses. Eighty-six percent of low-income children have a match. In the second column, children are also matched by physician. In this case, 33.6% of low-income children are matched. These estimates are again similar to those in Table 2, although the point estimates on SSRIs and mood stabilizers are somewhat larger.

Appendix Table A3 breaks the sample of children into those who were less than 12 or 12 plus during the period of universal drug coverage. All of the estimates are statistically significant and show the same patterns as in Table 2. In terms of effect sizes, younger children are more likely to be prescribed ADHD medications but less likely to be prescribed other types of psychotropic drugs. Hence, the effect of low income on being prescribed ADHD medication is proportionately larger for older children, while the effect of low income on being prescribed antipsychotics is proportionately larger for younger children. For example, the estimates suggest that low-income children less than 12 are 105% more likely to be prescribed antipsychotics while children 12 and over are 85% more likely to be prescribed antipsychotics if they are low income. The second panel of Appendix Table A3 shows that the effect of being low-income on polypharmacy is quite similar by age.

Table 7 looks more directly at the question of whether low-income children are more likely to receive prescriptions that are medically less appropriate. The table uses the same sample and follows the same format as Table 3. The first row of Table 7 is estimated using the subsample of children who do not have any diagnosis of either psychosis or conduct disorder. Even if we remove children with any diagnosis of psychosis or conduct disorders from the sample, low-income children are still 76% more likely to be prescribed antipsychotics.

The second row of Table 7 looks at whether children with a diagnosis of bipolar disorder were prescribed SSRIs. People with bipolar should not take SSRIs as they may provoke mania. This table suggests that low-income children with bipolar disorder are actually less likely to receive SSRIs, suggesting that their generally low probability of being prescribed SSRIs can be protective for this relatively small group of children.

Finally, the third row of Table 7 looks at the probability that a child received more than one prescription for benzodiazepines in a 30-day period. Benzodiazepines are addictive drugs and easily abused. Only very short-term use (typically less than a week) is recommended and then only for very specific indications. However, low-income children are 69% more likely to receive repeat benzodiazepine prescriptions. Hence, Table 7 suggests that low-income children do tend to receive prescriptions for antipsychotics and benzodiazepines that are medically less appropriate.

b) Area-level models

Table 8 presents estimates of equation (2) (Panel A) and equation (3) (Panel B) for the period of universal prescription drug coverage from January 2018 through March 2019. Panel A shows a comparison of the types of treatment received by children living in FSAs in the top quintile of the income distribution compared to treatment received by those living in FSAs in the bottom quintile. The middle three quintiles are the omitted category.

One important difference between these tables and those presented thus far is that Tables 2 through 6 are based on a sample of children who received mental health medications at some point. Table 8 provides a context for these results by looking at the fraction of all Ontario children who received various types of mental health services during the universal coverage period. This fraction can be computed by comparing those who received services to population numbers.

The means of the dependent variables show that 17.24% of Ontario children are estimated to have received some type of publicly-funded mental health care (other than medication) over this period. Most of that care was outpatient—17.02% of children received an outpatient visit for mental health, 1.63% had an ED visit for mental health, and 0.43% were hospitalized with a mental health condition. The last column shows that 38.95% of children who received non-medication treatment also filled a prescription for a mental health medication, consistent with Figure 2.

Turning to differences across area income levels, Panel A shows that children in FSAs in the bottom income quintile were less likely to receive any mental health care other than medication. This difference is largely because they were less likely to receive outpatient services. In high-income FSAs, children are significantly less likely to have mental health ED visits and mental health hospitalizations, perhaps because they have access to alternative services. Hence, these estimates suggest that differences in access to care across areas may be an important source of disparities in mental health treatment as the prior literature has emphasized. However, the results in Tables 2 through 8 show that area-level differences in access to services are not the whole story and that significant disparities remain conditional on local area mental health resources.

The last column of Panel A shows that conditional on receiving any non-medication mental health services, children in low-income FSAs are less likely to receive prescriptions for mental health drugs compared to children in middle-income FSAs. This pattern is inconsistent with the idea that low-income children receive more of most mental health medications because they are systematically sicker.

This pattern is also evident in Panel B. By focusing on differences in the utilization of mental health care by children living in high- and low-income areas *within* an FSA, these regressions are more similar in spirit to those in Tables 2 through 8. These tables suggest that there are no within-FSA differences in access to any non-drug mental health care or to outpatient care. Children in high-income parts of the FSA are however significantly less likely to have mental health visits at the hospital or ED, consistent with the between FSAs estimates. Within FSA, children in higher-income parts of the FSA are actually more likely to fill mental health medication prescriptions than children in middle- or low-income parts of their FSA conditional on receiving any form of non-medication mental health care. Again this pattern casts doubt on the idea that low-income children are prescribed more drugs mainly because they are sicker—among those receiving other mental health services, high-income children are actually more likely to be prescribed psychiatric medications.

Table 9 provides a bridge between the area-level regressions in Table 8 and the patient-year level regressions in the preceding tables by focusing on the types of medications received in the full sample of Ontario children during the expansion period when all children were covered by ODB. Again, Panel A shows estimates of equation (2) while Panel B shows estimates of equation (3).

Panel A shows that about 8% of all Ontario children filled a prescription for a mental health medication during the universal coverage period. The most common medications filled were ADHD medications (3.98% of children) and SSRIs (3.52% of children). But 1.34% of Ontario children received antipsychotics, 0.68% received non-SSRI antidepressants, 0.68% received benzodiazepines, and 0.46% received mood stabilizers (even though children with epilepsy have been excluded from the sample).

Like Panel A of Table 8, Panel A of Table 9 suggests that children in both higher- and lower-income FSAs are less likely to fill prescriptions for mental health medications compared to children in middle-income FSAs. In fact, we cannot reject the hypothesis that the effects are the same in the highest and lowest income FSAs. However, there are significant differences in the *composition* of mental health prescribing across high and low-income areas, with children in low-income areas being significantly more likely to receive antipsychotics and less likely to receive ADHD medications and mood stabilizers.

Looking *within* FSA in Panel B of Table 9, shows that children living in higher-income parts of an FSA are more likely to be prescribed any psychiatric medication. This difference is driven by significantly higher probabilities of receiving ADHD medications, SSRIs, and benzodiazepines. Children in the lower income parts of the FSA are significantly more likely to be prescribed antipsychotics.

Hence, the result that low-income children are more likely to receive antipsychotics is seen consistently whether we define low-income as living in a low-income FSA, living in a relatively low-income neighborhood within an FSA, or using our tagging method based on pre-expansion use of the ODB program.

VI. Discussion and Conclusions

There is a broad consensus that low-income people often receive less appropriate care than richer people conditional on need, but the reasons for that difference are unclear. We show that within local areas, the same providers treat richer and poorer patients differently conditional on diagnosis, even when all patients have the same health insurance and drug coverage.

Our study is set in Ontario, a Canadian province that has universal public health insurance for medical care, and most of our analyses focus on a period in which all children had publicly funded prescription drug coverage. We find that even within small areas in which children have similar geographic access to care, there are large differences in the way that low-income and higher-income children are treated when it comes to the prescribing of psychiatric medications.

Most strikingly, the same doctor is much more likely to prescribe antipsychotics to a low-income child than to a higher-income child with the same medical history and diagnoses. For example, the baseline estimate in column 6 of Table 2 indicates that low-income children are 76.3% more likely to be prescribed antipsychotics conditional on diagnosis. We also see that low-income children are more likely to be prescribed ADHD medications, mood stabilizers, and benzodiazepines in models that control for medical histories, diagnoses, and prescriber fixed effects, and they are less likely to be prescribed SSRI's, which are the first-line treatments for anxiety and depression.

These results are very robust to changes in the estimation period (e.g., including earlier years of the sample, or following groups of children for exactly the same period of time). And they are robust to other refinements to make the samples of low-income children as similar as possible to the sample of other children. Specifically, we try excluding children with either very high or very low medical expenditures, restrict the sample to children whose providers serve high, medium, and low-income children, and estimate models with exact matching of low-income to other children on the basis of age, postal area, diagnosis, and doctor. We also show that low-income children are more likely to receive prescriptions that may be medically inappropriate.

This pattern of results suggests that low-income children are more likely to receive powerful psychotropic drug treatments which can quickly alter their behaviors. In contrast, they are less likely to receive SSRIs, which act slowly, but arguably help to address underlying causes of behavior such as anxiety or depression. Discrimination or implicit bias on the part of providers may be one factor underlying these choices. But the existence of disparities in treatment does not prove the existence of such biases because there are many other possible reasons for disparities (Balsa and McQuire, 2003). One possibility is that low-income children face more serious consequences for disruptive behaviors (such as being suspended from school or referred to the criminal justice system). In addition, low-income children may be more likely to live in families who have less ability to deal with disruptive children (because for example, the parents work long or irregular hours and other childcare is not available).

These findings indicate that proposed solutions to the child mental health crisis such as increasing the number of specialty providers or increased screening of children are unlikely to eliminate disparities in care, and that measures aimed at changing the behaviors of individual providers, the supports available to family, and the broader treatment of children with mental health problems in schools and in the criminal justice system may also be necessary. Disentangling the reasons for the disparities in treatment, and the effectiveness of potential policy levers to address them are important avenues for future research.

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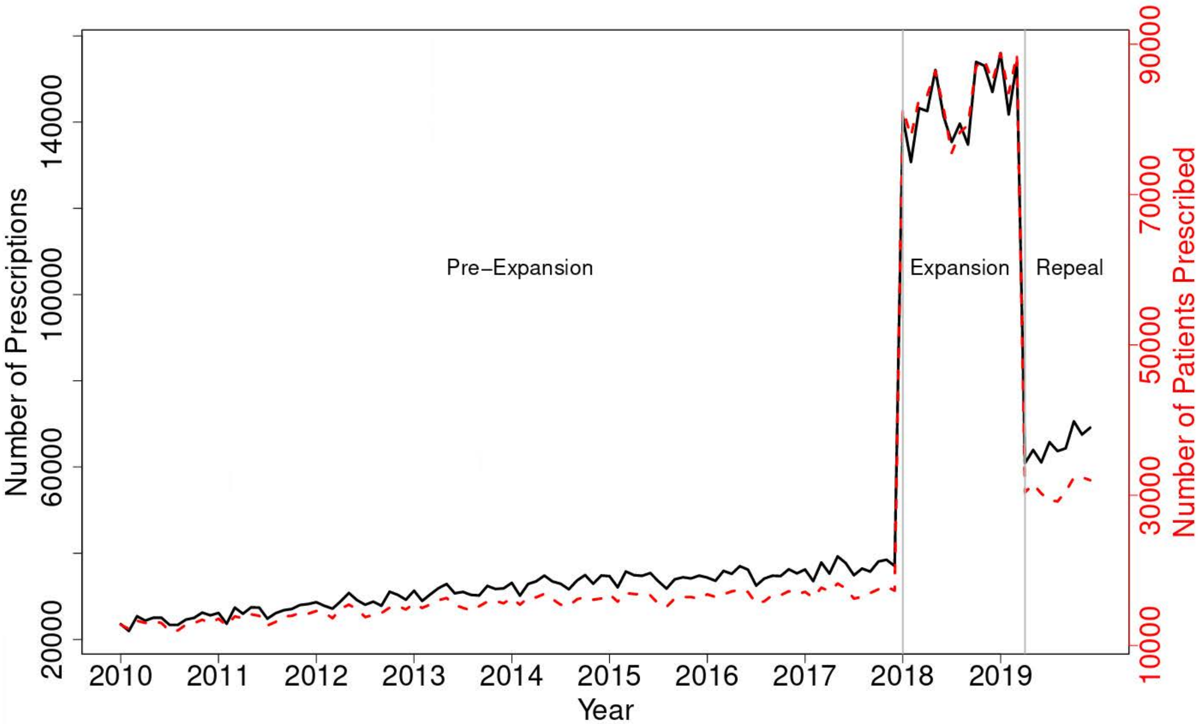
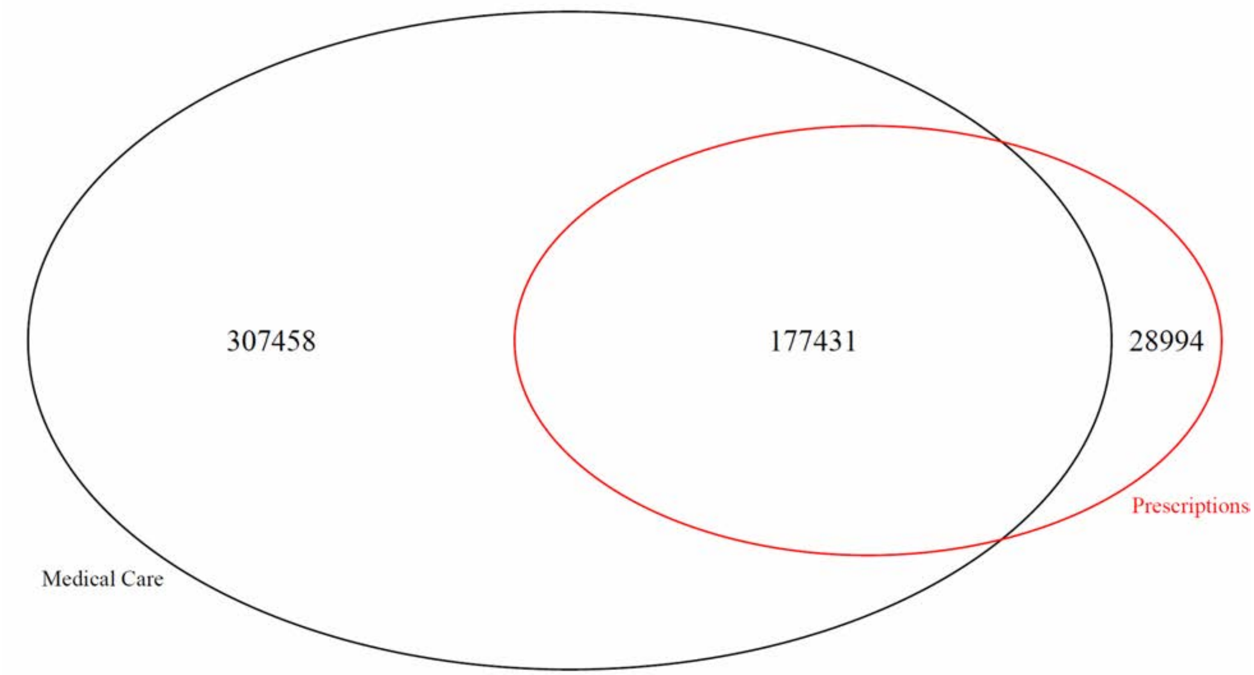
Figure 1. Time Series of Prescriptions and Patients Prescribed Between 2010 and 2019



Notes: This figure plots the monthly time series of number of mental health prescriptions over time on the left y-axis (in solid black) and number of patients prescribed mental health medication over time on the right y-axis (in dashed red). The grey vertical bars correspond to January 2018 and April 2019 corresponding to the initial OHIP+ expansion and the subsequent exclusion of children with private coverage dates.

Figure 2. Patients age 0-19 receiving mental health care in Ontario between January 2018 and March 2019, during the period of universal child drug coverage



Notes: We have data from ODB on all children who had a mental health prescription. In addition, we have the OHIP (Ontario Health Insurance Plan) records covering the non-drug medical care of all Ontario children. This Venn diagram shows the number of children who either received mental health prescriptions or had a mental health diagnosis in hospital-based or outpatient care ("medical care") between January 2018 and March 2019. Children with epilepsy are dropped from the sample since mood stabilizers and anti-convulsants may be appropriate for them but are also used as mental health drugs. 307,458 children received non-drug mental health care and did not receive a mental health prescription; 177,431 received both a prescription and non-drug mental health care; and 28,994 received a mental health prescription but did not receive any publicly funded, non-drug mental health care.

Table 1. Demographics, Fraction of Patient-Years Filling Prescriptions by Drug Class, and Medical History by Socioeconomic Status

	Low Income (1)	Privately Insured (High Income) (2)	Gained Coverage (Medium Income) (3)
Children (N)	46,027	142,631	34,698
Mental health prescriptions (N)	1,662,459	1,122,552	694,349
MH Prescriptions per patient-year	13.74	5.19	10.86
Polypharmacy:			
≥ 2 drugs in same month	0.506	0.343	0.473
≥ 3 drugs in same month	0.215	0.101	0.173
≥ 4 drugs in same month	0.088	0.031	0.065
Type Mental Health Prescriptions			
ADHD	0.589	0.500	0.527
Antipsychotics	0.290	0.112	0.207
SSRI	0.324	0.431	0.424
Other Antidepressants	0.114	0.102	0.113
Benzodiazepines	0.091	0.065	0.075
Mood Stabilizers & Anticonvulsants	0.093	0.047	0.066
Medical History			
Outpatient MH	0.714	0.668	0.827
Any MH diagnosis	0.696	0.645	0.801
Emergency department	0.413	0.362	0.413
MH emergency department	0.104	0.078	0.131
Inpatient hospitalization	0.079	0.054	0.073
MH hospitalization	0.036	0.021	0.047
Prior year medical spending (2019 dollars; median)	1,200	778	921
Area Level Income and Demographics at 1st observed prescription			
High income postal FSA	0.058	0.181	0.125
Rural dissemination area (DA)	0.125	0.112	0.147
Age at 1st prescription	13.70	14.94	13.92

Notes: This table summarizes the analysis sample of children who ever received an ODB-covered prescription between January 1, 2016 and December 31, 2019 for each type of patient. Low-income patients are those who filled any prescription prior to the OHIP+ expansion period (which began January 1, 2018). Privately-insured patients are those who filled a prescription only in the expansion period of universal ODB coverage (January 1, 2018 to March 31, 2019). The "gained coverage" group are those who fill a prescription only in the expansion and post-expansion periods suggesting that they were not low income, but retained their OHIP+ eligibility in the post-expansion period because they did not have private insurance. The three columns are mutually exclusive; there are also 20,929 unclassified patients (not shown) who filled their first prescription in the post-expansion period and who make up a fourth category that exhausts the sample. The number of patients and prescriptions, the fraction of patient-years with a particular prescription, and medical and emergency department/hospitalization diagnosis indicators are measured at the patient-year-level.

Table 2: Prescribing to Low-Income Children vs. All Others During the Period of Universal Child Drug Coverage, Jan. 2018-March 2019

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.499	0.135***	0.066***	0.064***	0.049***	0.051***
		(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Antipsychotics	0.160	0.164***	0.166***	0.152***	0.133***	0.122***
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
SSRI	0.438	−0.114***	−0.055***	−0.041***	−0.040***	−0.028***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Other Antidepressants	0.122	0.001	0.020***	0.013***	0.021***	0.022***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Benzodiazepines	0.088	0.013***	0.025***	0.017***	0.026***	0.024***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mood Stabilizers	0.058	0.047***	0.050***	0.037***	0.053***	0.031***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Panel B. Polypharmacy: number of unique mental health drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
≥ 2 drugs	0.435	0.156***	0.152***	0.139***	0.138***	0.130***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
≥ 3 drugs	0.154	0.126***	0.127***	0.114***	0.109***	0.102***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
≥ 4 drugs	0.056	0.068***	0.070***	0.061***	0.057***	0.053***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: Panel A displays the output of patient-level regressions of being prescribed a drug of a given class (in rows of the first column) on whether the patient is low income. The coefficient on low income is displayed; each entry is a coefficient from a separate regression. Low income children are characterized as those who are prescribed between January 2016 and December 2017. Non low income children are those prescribed after January 2018 and not before. This regression compares low income and non low income prescriptions during the expansion period. Panel B displays analogous outputs but with polypharmacy outcomes. Polypharmacy is an indicator for whether the child is ever prescribed greater than a certain number of unique mental health drugs in a calendar month. Column 1 shows the mean for each outcome indicator. Columns 2 to 6 sequentially add additional controls: forward sortation area (FSA) fixed effects; demographic controls (sex and age); indicators for prior 30 day emergency department (ED), ED mental health, ED injury, hospitalization, hospitalization for mental health, hospitalization for injury, and mental health outpatient visit, and prior 1 year of the same variables, along with log prior year cost plus one; two most recent mental health diagnosis ICD codes in the past year (across all encounters and settings), and nine dummies for ever being diagnosed with psychosis, anxiety, depression, bipolar/mania, conduct disorder, developmental, intellectual, ADHD, and substance use disorder diagnoses; and fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. Other antidepressants include tricyclic antidepressants, monoamine oxidase inhibitors, and serotonin norepinephrine reuptake inhibitors (SNRIs). N=206,425. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 3: Prescribing to Low-Income Children in Jan. 2016—Dec. 2017 vs. Prescribing to All Others in Jan. 2018—Mar. 2019

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.486	0.074***	0.015***	0.022***	0.019***	0.016***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Antipsychotics	0.166	0.141***	0.141***	0.128***	0.120***	0.104***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SSRI	0.443	−0.106***	−0.048***	−0.042***	−0.032***	−0.023***
		(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Other Antidepressants	0.128	0.004***	0.022***	0.014***	0.016***	0.013***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Benzodiazepines	0.094	0.026***	0.035***	0.025***	0.026***	0.021***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mood Stabilizers	0.060	0.042***	0.042***	0.030***	0.030***	0.021***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.002)	(0.001)

Panel B. Polypharmacy: number of unique mental health drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.438	0.098***	0.091***	0.081***	0.079***	0.072***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\geq$ 3 drugs	0.155	0.083***	0.083***	0.072***	0.071***	0.063***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\geq$ 4 drugs	0.055	0.046***	0.048***	0.041***	0.040***	0.035***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: Panel A displays the output of patient-level regressions of being prescribed a drug of a given class (in rows of the first column) on whether the patient is low income. The coefficient on low income is displayed; each entry is a coefficient from a separate regression. Low income children are characterized as those who are prescribed between January 2016 and December 2017. Non low income children are those prescribed after January 2018 and not before. This regression compares low income individuals between January 2016-December 2017 to non low income individuals after January 2018. Panel B displays analogous outputs but with polypharmacy outcomes. Polypharmacy is an indicator for whether the child is ever prescribed greater than a certain number of unique mental health drugs (based on Drug Identification Number) in a calendar month. Column 1 shows the mean for each outcome indicator. Columns 2 to 6 sequentially add additional controls: forward sortation area (FSA) fixed effects; demographic controls (sex and age); indicators for prior 30 day emergency department (ED), ED mental health, ED injury, hospitalization, hospitalization for mental health, hospitalization for injury, and mental health outpatient visit, and prior 1 year of the same variables, along with log prior year cost plus one; two most recent mental health diagnosis ICD codes in the past year (across all encounters and settings), and nine dummies for ever being diagnosed with psychosis, anxiety, depression, bipolar/mania, conduct disorder, developmental, intellectual, ADHD, and substance use disorder diagnoses; and fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. Other antidepressants include tricyclic antidepressants, monoamine oxidase inhibitors, and serotonin norepinephrine reuptake inhibitors (SNRIs). N=230,683. * p<0.1; ** p<0.05; *** p<0.01.

Table 4: Prescribing to Children with 2+ Prescriptions in a 15-Month Period (Oct. 2016—Dec. 2017 for Low-Income; Oct. 2018—Dec. 2019 for Gained Coverage; Jan. 2018—Mar. 2019 for High-Income).

Panel A. Prescribing of Drug Class

	ADHD	Anti-psychotics	SSRI	Other anti-depressant	Benzo-diazepine	Mood stabilizers & anticonvulsants
	(1)	(2)	(3)	(4)	(5)	(6)
Low Income	0.002	0.102***	−0.034***	0.015***	0.018***	0.017***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Gained Coverage	−0.012***	0.041***	0.009***	0.006***	0.007***	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Mean Dep. Var.	0.530	0.171	0.444	0.121	0.079	0.061
R^2	0.609	0.305	0.5342	0.249	0.238	0.466
N =	171,406	171,406	171,406	171,406	171,406	171,406

Panel B. Polypharmacy: number of unique mental health drugs in a month

	Number of Unique Drugs:		
	≥ 2	≥ 3	≥ 4
	(1)	(2)	(3)
Low Income	0.066***	0.069***	0.035***
	(0.004)	(0.003)	(0.002)
Gained Coverage	0.031***	0.029***	0.018***
	(0.004)	(0.004)	(0.002)
Mean Dep. Var.	0.499	0.178	0.064
R^2	0.190	0.198	0.174
N =	171,406	171,406	171,406

Notes: This table displays the output of patient-level regressions of the likelihood of being prescribed a drug of a given class (Panel A) and filling multiple unique drugs in the same month (Panel B) across different types of patients. Privately insured (the omitted category) receive at least two prescriptions between January 1, 2018 and March 31, 2019 (expansion period) only. Gained coverage receive at least one prescription between October 1, 2018 and March 31, 2019 and at least one prescription between April 1, 2019 and December 31, 2019, and no prescriptions prior to January 1, 2018. Low income individuals receive at least two prescriptions between October 1, 2016 and December 31, 2017. The analysis sample includes all prescription during the relevant periods for each patient type. All regressions include controls for log one plus prior year cost, fixed effects for age, sex, forward sortation area (FSA), indicators for prior 30 day emergency department (ED), ED mental health, ED injury, hospitalization, hospitalization for mental health, hospitalization for injury, and mental health outpatient visit, and prior 1 year of the same variables, along with log prior year cost plus one; two most recent mental health diagnosis ICD codes in the past year (across all encounters and settings), and nine dummies for ever being diagnosed with psychosis, anxiety, depression, bipolar/mania, conduct disorder, developmental, intellectual, ADHD, and substance use disorder diagnoses; and fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. Other antidepressants include tricyclic antidepressants, monoamine oxidase inhibitors, and serotonin norepinephrine reuptake inhibitors (SNRIs). * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 5: Prescribing to Low-income vs. All Others During the Period of Universal Child Drug Coverage, Jan. 2018—Mar. 2019 Including Only Children Prescribed by Physicians Who Treated all Three Income Groups)

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.567	0.103***	0.063***	0.064***	0.059***	0.063***
		(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
Antipsychotics	0.187	0.162***	0.165***	0.154***	0.135***	0.131***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
SSRI	0.391	−0.082***	−0.047***	−0.035***	−0.044***	−0.032***
		(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Other Antidepressants	0.114	0.008***	0.020***	0.015***	0.022***	0.024***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Benzodiazepines	0.080	0.019***	0.027***	0.018***	0.025***	0.026***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Mood Stabilizers	0.065	0.044***	0.047***	0.032***	0.049***	0.031***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.003)	(0.002)

Panel B. Polypharmacy: number of unique drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.481	0.151***	0.152***	0.141***	0.144***	0.146***
		(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$\geq$ 3 drugs	0.181	0.128***	0.130***	0.117***	0.114***	0.114***
		(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
$\geq$ 4 drugs	0.068	0.071***	0.073***	0.064***	0.061***	0.060***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: This table repeats the analysis in the table comparing low income to others during the period of universal child drug coverage (Table 2), restricting to patients whose modal prescriber treats both low income and non low income children. Specifically, prescribers who treat at least 10 low income and non low income children during the expansion period. This drops the number of unique physicians from 16,495 to 4,526 and the number of children from 206,425 to 146,697. * p<0.1; ** p<0.05; *** p<0.01.

Table 6: Comparing Low-income and other children with exact matching during the period of universal drug coverage

Panel A. Prescribing of Drug Class

	Age, Sex FSA, Comorbidities (1)	Including Physician ID (2)
ADHD	0.067***	0.054***
	(0.003)	(0.006)
Antipsychotics	0.127***	0.116***
	(0.002)	(0.005)
SSRI	−0.072***	−0.040***
	(0.003)	(0.005)
Other Antidepressants	0.017***	0.014***
	(0.002)	(0.003)
Benzodiazepines	0.018***	0.012***
	(0.002)	(0.003)
Mood Stabilizers	0.055***	0.024***
	(0.001)	(0.003)

Panel B. Polypharmacy: number of unique mental health drugs in a month

	Age, Sex FSA, Comorbidities (1)	Including Physician ID (2)
≥ 2 drugs	0.123***	0.099***
	(0.003)	(0.006)
≥ 3 drugs	0.104***	0.093***
	(0.002)	(0.004)
≥ 4 drugs	0.054***	0.047***
	(0.001)	(0.003)

Notes: This table presents the result of an exact matching exercise (analogous to Table 2) where low income children are matched to non-low income children. In column 1, low income children are matched to non-low income children of the same sex, FSA, age bin (0-1; 2-4; 5-9; 10-13; and 14+), and nine "ever diagnosed" mental health comorbidities (psychosis, anxiety, depression, bipolar/mania, conduct disorder, developmental, intellectual, ADHD, and substance use disorder). In column 2, children are also matched on being treated by the same modal physician. Ordinary linear regressions are then estimated on whether comparable low and non-low income children are prescribed a drug of a certain class during the expansion period. 86.0% of low income children are matched in column 1 (25,619 low income children matched to 158,950 non-low income children) and 33.6% of low income children are matched in column 2 (10,002 low income children matched to 24,426 non-low income children). * p<0.1; ** p<0.05; *** p<0.01.

Table 7: Possibly Medically Inappropriate Prescribing to Low-Income Children in Jan. 2016—Dec. 2017 vs. Prescribing to All Others in Jan. 2018—Mar. 2019

	N	Mean Dep. Var.	Sequentially Adding Controls: FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Antipsychotics for children w/o psychosis or conduct	138,619	0.108	0.104***	0.106***	0.100***	0.098***	0.081***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SSRI to bipolar	10,567	0.727	−0.110***	−0.087***	−0.067***	−0.040***	−0.019*
			(0.012)	(0.012)	(0.013)	(0.012)	(0.016)
Repeat benzodiazepines (30 days)	230,683	0.026	0.025***	0.027***	0.022***	0.021***	0.018***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: This table displays the likelihood of receiving medically inappropriate prescribing on whether the patient is low income (following the same definitions and format as Table 3). The medically inappropriate prescribing proxies are displayed in the rows and are constructed for the relevant subpopulation. For instance, the first outcome (row 1) focuses on the sample of children without a psychosis or conduct diagnosis and the outcome is whether they receive an antipsychotic prescription. Note that the 3 digit ICD-9 codes for bipolar and obsessive compulsive disorder cannot be differentiated from other disorders; therefore, we focus on a conservative sample of children whom we know definitely do not have those diagnoses. The coefficient on low income is displayed; each entry is a coefficient from a separate regression. Low income children are characterized as those who are prescribed between January 2016 and December 2017. Non low income children are those prescribed after January 2018 and not before. This regression compares low income individuals between January 2016-December 2017 to non low income individuals after January 2018. Column 1 shows the mean for each outcome indicator. Columns 2 to 6 sequentially add additional controls: forward sortation area (FSA) fixed effects; demographic controls (sex and age); indicators for prior 30 day emergency department (ED), ED mental health, ED injury, hospitalization, hospitalization for mental health, hospitalization for injury, and mental health outpatient visit, and prior 1 year of the same variables, along with log prior year cost plus one; two most recent mental health diagnosis ICD codes in the past year (across all encounters and settings), and nine dummies for ever being diagnosed with psychosis, anxiety, depression, bipolar/mania, conduct disorder, developmental, intellectual, ADHD, and substance use disorder diagnoses; and fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. N=230,683. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 8: Probability of Receiving Mental Health Care in a Particular Setting in Low-Income vs. High-Income Areas (FSA and DA) Under Universal Prescription Coverage, Jan. 2018—Mar. 2019.

Panel A. Likelihood of Mental Health Care by FSA Income Quintile

Dep Var: ×100	Any Non-Drug MH Care (1)	MH Outpatient (2)	MH ED (3)	MH Hospital (4)	Prescribed MH Drug cond. on MH Care (5)
FSA Income: Top quintile	0.60 (0.45)	0.68 (0.45)	-0.50^{***} (0.09)	-0.12^{***} (0.03)	-5.13^{***} (1.35)
FSA Income: Bottom quintile	-0.98^{**} (0.43)	-1.00^{**} (0.43)	-0.09 (0.09)	0.04 (0.03)	-7.62^{***} (1.31)
Top=Bottom Quintile? (p-value)	0.002	< 0.001	< 0.001	< 0.001	0.065
Mean Dep Var (×100)	17.24	17.02	1.63	0.43	38.95
R^2	0.02	0.02	0.05	0.04	0.07
N =	513	513	513	513	513

Panel B. Likelihood of Mental Health Care by DA Income Quintile (within a FSA)

Dep Var: ×100	Any Non-Drug MH Care (1)	MH Outpatient (2)	MH ED (3)	MH Hospital (4)	Prescribed MH Drug cond. on MH Care (5)
DA Income: Top quintile	1.61 (1.05)	1.61 (1.04)	-0.02 (0.08)	-0.01 (0.02)	2.02^{***} (0.49)
DA Income: Bottom quintile	0.12 (1.05)	0.06 (1.04)	0.35^{***} (0.11)	0.10^{***} (0.03)	0.77 (0.61)
Top=Bottom Quintile? (p-value)	0.161	0.147	0.003	0.006	0.058
Mean Dep Var (×100)	17.17	16.95	1.60	0.42	39.77
R^2	0.06	0.06	0.22	0.21	0.79
N =	2,565	2,565	2,565	2,565	2,565

Notes: Panel A shows the estimated coefficients from forward sortation area (FSA)-level regression of the fraction of children and youth receiving mental health care across (across multiple settings) on an indicator for the top and bottom income quintile of the FSA during the expansion period: January 1, 2018 to March 31, 2019. Panel B splits each FSA into five quintiles based on the income of the dissemination area (DA) the patient resides in. A linear regression of the fraction of children and youth receiving mental health care on whether the DA is in the top or bottom income quintile is estimated. Dissemination areas are small areas with populations of 400-700 people composed of one or more neighboring blocks and is the smallest standard geographic area for which all census data are disseminated. The outcome in column 5 is the fraction prescribed a mental health drug conditional on receiving non-drug mental health care. The regressions in panel B include FSA fixed effects, are weighted by FSA age 0-19 population, and standard errors are clustered at the FSA-level. * p<0.1; ** p<0.05; *** p<0.01.

Table 9: Probability of Being Prescribed a Medication in a Particular Class in Low-Income vs. High-Income Areas within FSAs Under Universal Child Prescription Drug Coverage, Jan. 2018—Mar. 2019.

Panel A. Likelihood of Being Prescribed a Medication in a Particular Drug Class by FSA Income Quintile

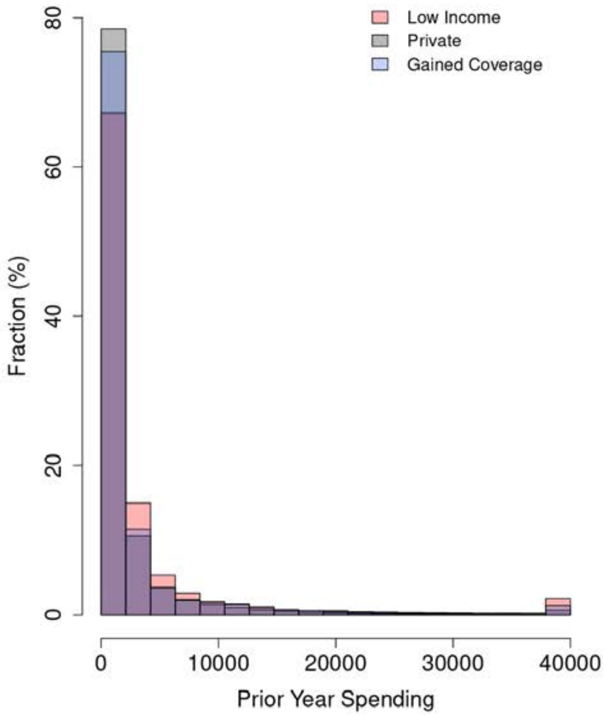
Dep Var: ×100	Any Rx (1)	ADHD (2)	Antipsychotics (3)	SSRI (4)	Other Antidepressant (5)	Benzo -diazepines (6)	Mood Stabilizers & Anticonvulsants (7)
FSA Income:	−1.14***	−0.30	−0.58***	−0.63***	−0.12**	−0.10**	−0.10***
Top quintile	(0.37)	(0.20)	(0.09)	(0.18)	(0.05)	(0.05)	(0.02)
FSA Income:	−1.58***	−0.79***	−0.06	−0.90***	−0.15***	−0.12**	−0.02
Bottom quintile	(0.36)	(0.20)	(0.09)	(0.17)	(0.05)	(0.05)	(0.02)
Top=Bottom Quintile? (p-value)	0.16	0.02	< 0.01	0.11	0.29	0.41	0.04
Mean Dep Var (×100)	8.04	3.98	1.34	3.52	0.68	0.68	0.46
R^2	0.04	0.03	0.08	0.06	0.02	0.02	0.03
N =	513	513	513	513	513	513	513

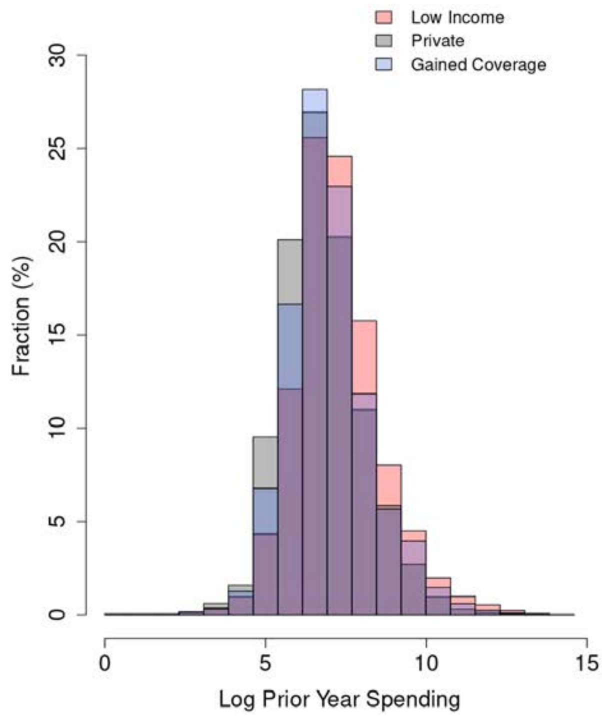
Panel B. Likelihood of Being Prescribed a Medication in a Particular Drug Class by DA Income Quintile (within a FSA)

Dep Var: ×100	Any Rx (1)	ADHD (2)	Antipsychotics (3)	SSRI (4)	Other Antidepressant (5)	Benzo -diazepines (6)	Mood Stabilizers & Anticonvulsants (7)
DA Income:	1.16***	0.75***	−0.10*	0.54***	0.07*	0.10**	0.01
Top quintile	(0.43)	(0.23)	(0.05)	(0.19)	(0.04)	(0.04)	(0.02)
DA Income:	0.08	0.14	0.39***	−0.22	0.03	−0.03	0.05*
Bottom quintile	(0.36)	(0.19)	(0.08)	(0.15)	(0.03)	(0.03)	(0.03)
Top=Bottom Quintile? (p-value)	0.03	0.03	< 0.01	< 0.01	0.20	0.01	0.12
Mean Dep Var (×100)	10.03	3.95	1.32	3.49	0.67	0.67	0.46
R^2	0.20	0.27	0.40	0.29	0.35	0.21	0.17
N =	2,565	2,565	2,565	2,565	2,565	2,565	2,565

Notes: Panel A shows the estimated coefficients from forward sortation area (FSA)-level regression of the fraction of children and youth prescribed each drug class on an indicator for the top and bottom income quintile of the FSA during the expansion period: January 1, 2018 to March 31, 2019. Panel B splits each FSA into five quintiles based on the income of the dissemination area (DA) the patient resides in. A linear regression of the fraction of children and youth prescribed each drug class on whether the DA is in the top or bottom income quintile is estimated. Dissemination areas are small areas with populations of 400-700 people composed of one or more neighboring blocks and is the smallest standard geographic area for which all census data are disseminated. The regressions in panel B include FSA fixed effects, are weighted by FSA age 0-19 population, and standard errors are clustered at the FSA-level. Other antidepressants include tricyclic antidepressants, monoamine oxidase inhibitors, and serotonin norepinephrine reuptake inhibitors (SNRIs). * p<0.1; ** p<0.05; *** p<0.01.

Appendix Figure A1: Distribution of Healthcare Spending by Patient Type





Notes: The left figure plots the distribution of prior year medical spending and right figure shows the log of spending plus $1 for the three patient types: low income, gained coverage, and privately insured. Spending is winsorized at $40,000 CAD. The sample corresponds to the one used in Table 1: patient-years with at least any mental health prescription between January 1, 2016 and December 31, 2019.

Table A1: Regressions similar to Table 2 but adding controls in a different order

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	Age & Sex	Prior Medical Utilization	Diagnosis Controls	FSA	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.499	0.053***	0.055***	0.038***	0.049***	0.051***
		(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Antipsychotics	0.160	0.177***	0.164***	0.145***	0.133***	0.122***
		(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
SSRI	0.438	−0.045***	−0.032***	−0.028***	−0.040***	−0.028***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Other Antidepressants	0.122	0.017	0.025***	0.021***	0.021***	0.022***
		(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Benzodiazepines	0.088	0.023***	0.014***	0.022***	0.026***	0.024***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mood Stabilizers	0.058	0.049***	0.034***	0.049***	0.053***	0.031***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Panel B. Polypharmacy: number of unique mental health drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	Age & Sex	Prior Medical Utilization	Diagnosis Controls	FSA	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.435	0.147***	0.136***	0.135***	0.138***	0.130***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\geq$ 3 drugs	0.154	0.124***	0.112***	0.107***	0.109***	0.102***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\geq$ 4 drugs	0.056	0.069***	0.061***	0.057***	0.057***	0.053***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: This table repeats the analysis in the table comparing low income to others during the period of universal child drug coverage (Table 2), sequentially adding controls in a different order. * p<0.1; ** p<0.05; *** p<0.01.

Appendix Table A2: Repeating Table 2 Excluding Children with the Top and Bottom 5% of Healthcare Costs

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.518	0.162***	0.070***	0.073***	0.057***	0.056***
		(0.005)	(0.004)	(0.003)	(0.004)	(0.003)
Antipsychotics	0.143	0.159***	0.160***	0.123***	0.109***	0.106***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
SSRI	0.430	−0.120***	−0.041***	−0.047***	−0.044***	−0.033***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Other Antidepressants	0.115	−0.005*	0.019***	0.004	0.012***	0.016***
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Benzodiazepines	0.078	−0.006***	0.009***	0.002***	0.010***	0.010***
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Mood Stabilizers	0.051	0.025***	0.029***	0.009***	0.025***	0.015***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Panel B. Polypharmacy: number of unique mental health drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical Utilization	Diagnosis Controls	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.427	0.147***	0.138***	0.090***	0.090***	0.098***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\geq$ 3 drugs	0.142	0.114***	0.112***	0.076***	0.073***	0.078***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\geq$ 4 drugs	0.048	0.057***	0.058***	0.039***	0.037***	0.039***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Notes: This table repeats the analysis in the table comparing low income to others during the period of universal child drug coverage (Table 2), excluding patients in the bottom and top 5% of prior year medical spending. The top and bottom 5% correspond to \$9,637 and \$130 respectively. N=185,849. * p<0.1; ** p<0.05; *** p<0.01.

Appendix Table A3: Repeating Table 2 by age of the child

Panel A. Prescribing of Drug Class

	Ages < 12		Ages ≥ 12	
	Mean (Non-Low Income)	Low Income Coefficient	Mean (Non-Low Income)	Low Income Coefficient
	(1)	(2)	(3)	(4)
ADHD	0.832	0.048***	0.356	0.056***
		(0.004)		(0.004)
Antipsychotics	0.119	0.125***	0.140	0.119***
		(0.006)		(0.004)
SSRI	0.115	−0.029***	0.576	−0.028***
		(0.004)		(0.004)
Other Antidepressants	0.025	0.013***	0.156	0.031***
		(0.002)		(0.004)
Benzodiazepines	0.034	0.009***	0.105	0.030***
		(0.002)		(0.003)
Mood Stabilizers	0.053	0.011***	0.051	0.037***
		(0.002)		(0.002)

Panel B. Polypharmacy: number of unique mental health drugs in a month

	Ages < 12		Ages ≥ 12	
	Mean (Non-Low Income)	Low Income Coefficient	Mean (Non-Low Income)	Low Income Coefficient
	(1)	(2)	(3)	(4)
≥ 2 drugs	0.447	0.113***	0.401	0.137***
		(0.007)		(0.004)
≥ 3 drugs	0.130	0.088***	0.138	0.107***
		(0.005)		(0.004)
≥ 4 drugs	0.034	0.037***	0.050	0.058***
		(0.003)		(0.003)

Notes: This table repeats the analysis in the table comparing low income to others during the period of universal child drug coverage (Table 2) for children ages < 12 and ≥ 12. All controls are included: forward sortation area (FSA) fixed effects; demographic controls (sex and age); indicators for prior 30 day emergency department (ED), ED mental health, ED injury, hospitalization, hospitalization for mental health, hospitalization for injury, and mental health outpatient visit, and prior 1 year of the same variables, along with log prior year cost plus one; two most recent mental health diagnosis ICD codes in the past year (across all encounters and settings); and fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. * p<0.1; ** p<0.05; *** p<0.01.