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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. The analysis takes advantage of an expansion to universal public drug coverage followed by a contraction in access, coupled with rich administrative data that includes 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 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. Hence universal drug coverage for children did not eliminate differences in prescribing practices between low-income and higher income children, suggesting that addressing these differences would require additional interventions including changing prescribing behaviors of individual providers.

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People of different 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). While low-income individuals tend to consume more care, they are on average sicker: Holding measures of need constant, people with lower income are generally less likely to receive appropriate care (Cutler and Lleras-Muney, 2010). The 2016 U.S. National Healthcare Quality and Disparities Report for example, examines several indicators of the adequacy of care and concludes that poor people have worse access to care than richer people on most measures. Such disparities have also been found in countries like Canada with universal health care (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.

We examine disparities in the care received by children who received publicly funded pharmaceutical treatment for mental health problems in the province of Ontario, Canada between 2010 and 2019. 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 children's outcomes, much 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 even when they gain 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 take advantage of detailed administrative data that tracks children's health care utilization in conjunction with two sharp changes in the design of Ontario's public prescription medication coverage program. All Canadians are covered by universal public health insurance programs administered by provincial governments that cover most inpatient and outpatient care. But coverage of medications is not universal. In Ontario before Jan. 1, 2018, only low-income children had free public medication coverage. But between Jan. 1, 2018 and March 31, 2019, Ontario provided free universal medication coverage to all children (no premiums, no deductibles, no copayments). For the first time, millions of children were eligible for free prescription medications and no active "take up" of the program was necessary—pharmacies were responsible for billing the government. However, this program was subsequently cut back, and after April 30, 2019 only children without private medication coverage (generally offered by parent's employers) were covered by the government medication plan.

[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.

We use these changes to identify three groups of children: Low-income children who had medication coverage prior to the change; Children who would otherwise have private medication coverage but who have public 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 likely have incomes above the low-income cutoffs. On average these groups can be thought of as corresponding to low, high, and medium-income families, respectively. We mainly focus on within-area differences in care, while documenting that there are also large between-area differences in care, that may be due at least in part to differences in the availability of mental health services.

Using these three groups of children we show that compared to higher-income children, low-income children are more likely to be prescribed inappropriately. Low-income children are more likely to be prescribed antipsychotics and most of this prescribing is "off label," i.e., not approved by the Food and Drug Administration for the diagnoses they have. Low-income children are also 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. Low-income children are also more likely to receive benzodiazepines, and they are more likely to get repeated benzodiazepine prescriptions. This is concerning given that benzodiazepines are addictive, and only very short courses, for very particular circumstances, are ever recommended for children.[2] Low-income children are also slightly more likely to be prescribed medications for ADHD. Finally, low-income children are more likely to be prescribed, two, three, or four plus mental

[2] Benzodiazepines are used to treat seizures in epileptic children, but, as discussed below, we have excluded children with epilepsy from our sample. Short courses are also used to treat anxiety about dental or surgical procedures in children, but are not recommended for the management of anxiety outside a clinical setting (Kuang et al., 2017).

health medications (a measure of "polypharmacy") within a single month compared to higher-income children.

In addition to documenting these disparities in mental health treatment, we shed light on some of 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 (i.e., within dissemination areas defined as blocks of 400 to 700 persons by the Canadian census), suggesting that they cannot be explained differences in the supply of different types of providers at the local level. Some of the differences are explained by children's prior medical history and diagnoses. But even conditional on these factors, large differences in treatment within areas remain. Finally, we show that differences in treatment persist when physician fixed effects are included in the model which indicates that the same doctors are treating children with the same diagnoses and medical histories differently when they are from low-income and higher-income families.

These findings suggest that simply extending medication coverage did not resolve socioeconomic differences in prescribing patterns and that more targeted measures may be needed. Our findings also suggest that analyses focusing on broad proxies for socioeconomic status (such as those using zip codes to proxy for income) will miss much of the variation in treatment practices. This conclusion highlights the strength of our research setting which allows us to classify individuals by income without income linkages and study differential treatment practices under the identical prescription plan. 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 over many years.[3]

The rest of our paper proceeds as follows: Section II distills some of the most relevant background information from the vast literature on socioeconomic disparities in health care which informs our study. 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 and conclusions.

II. Background

While there is little dispute about the existence of disparities, it has been more difficult to document their causes. Much of the disparities research in health economics has been informed by the Grossman (1972, 2006) model of investments in health capital and the resulting derived demands for health inputs such as preventive care. The model suggests many possible demand-side reasons why the poor receive less care than richer people with a similar health status.

Most obviously, low-income individuals are more likely to be financially constrained, especially if they lack adequate health insurance. For example, 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 if, for example, they have less flexibility at work, worse access to transportation, or less ability to pay transportation costs (Acton, 1975; Smith et al. 2022). Low-income individuals may have different time preferences or attitudes towards risk compared to

[3] It would be possible to conduct a similar analysis in many European settings, but rates of child psychiatric drug use tend to be lower in European settings, and prescription guidelines are more proscriptive. Hence, there may be less scope for variation in individual doctor's practice styles in these settings.

others (Fuchs, 1982). Or they may simply have worse information about the benefits of medical care (Lleras-Muney and Glied, 2008). More subtly, some low-income individuals may have lower levels of trust in medical authorities and may therefore be slower to seek medical advice and less likely to follow up on recommendations for additional care (Alsan and Wannamaker, 2018; Alsan et al., 2019).

However, there is increasing evidence that supply-side factors also drive disparities in treatment (Chandra and Skinner, 2004). For example, 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 shortages of qualified health professionals is especially prominent in discussions of child mental health treatment. For example, Findling and Stepanova (2018) and McBain et al. (2019) highlight severe shortages of child psychiatrists in the United States. Fremont et al. (2008) conclude that such shortages force pediatricians and 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.

A third explanation for health care disparities is that the same providers provide different treatment to poor patients, an explanation that falls outside the classical supply-demand framework. For example, Brekke et al. (2018) study diabetic patients in Norway and find that doctors provide fewer services to less educated and lower income patients. Meliyanni et al. (2013) study waiting times in Australian public hospitals and find that conditional on clinical factors, patients of higher socioeconomic status had systematically lower waiting times. Moscelli et al. (2018) report similar findings for hospitals in the English National Health Service. They estimate that only 12% of the variation in wait times can be explained by the patient's choice of hospital with the remaining 88% reflecting within-hospital differences in treatment. Hajizedeh (2018) find that the poor in Canada also wait longer for appointments. Angerer et al. (2019) conduct an audit study in Austria in which mock patients sent email seeking to book doctor's appointments. The emails signaled whether the patient had a doctorate or medical degree. The authors found that physicians responded more quickly, and offered lower wait times, when the patients signaled that they possessed an advanced degree.

Our work is informed by this literature. We first document that there are large disparities in the treatment of children in higher- and lower-income areas—demonstrating what researchers would find if they used areas to proxy for income. However, we then show that area-level differences cannot be the whole story because there are also large within-area differences in treatment. These within-area differences persist when we control for detailed patient characteristics. Most tellingly, they persist when we examine patients who see the same providers during the same universal prescription coverage period. These findings suggest that interactions between individual providers and their patients are an important source of disparities in care.

III. Data

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 Medication Benefit (ODB) program. In this paper, 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. Data is provided by ICES.[4] Children and youth are defined as those who were less than 20 years of age at the time we first observe a prescription for a mental health medication. In addition to the rich patient-level administrative data, a key advantage of our data is that we can go beyond trying to infer children's household income using area-level income measures. These datasets were linked using unique encoded identifiers and analyzed at ICES. Policy changes allow us to classify children into household income categories from their eligibility for the ODB program.

Public coverage of prescription medications for children under ODB changed dramatically in 2018. Prior to January 2018, only children in households eligible for financial support under the Ontario Works or Ontario Disability Support Program were eligible. These programs provide income support to low-income households. In 2022 the income cutoffs for Ontario Works were $10,000 (Canadian Dollars) for a single person, $15,000 for a couple, plus $500 for each dependent. Under the Ontario Disability Support Program, a family with two adults and a child under 17 would be eligible for a basic needs allowance of $1,341 and a

[4] 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.

maximum shelter benefit of $846 per month.[5] These cutoffs indicate that only the lowest-income households were eligible for this benefit, similar to Medicaid coverage in the United States.

In January 2018, the government suddenly announced that all Ontarians under 25 would receive free coverage of any medications in the ODB formulary under a rebranded plan called OHIP+. The number of children using 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 suggests that over the course of a year and with full medication coverage, about half of Ontario children would need to have a prescription filled. Take-up was not an issue with OHIP+ because it was not necessary for people to enroll—all children were eligible and pharmacists knew to bill the government directly.[6] However, April 2019 saw retrenchment 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).[7]

Figure 1 shows the number of mental health prescriptions and the number of children receiving a mental health prescription paid for by the Ontario Medication Benefit over the

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[5] See https://www.ontario.ca/page/eligibility-ontario-works-financial-assistance for information about Ontario Works and https://www.ontario.ca/document/ontario-disability-support-program-policy-directives-income-support/61-basic-needs for information about the Ontario Disability Support Program.

[6] 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 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.

[7] It would be reasonable to ask why parents didn't just turn down private medication coverage, if offered, and keep their children on OHIP+? The main reason is likely that parents needed their own medication coverage, and 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.

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. In particular, prior to OHIP+, only children in low-income households were covered. Once all children became covered, the sample becomes more representative of all children in the province, while 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 lower part of the income distribution (Barnes and Anderson, 2015).

We take advantage of this strong selectivity 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, children who only appear in the sample after January 2018, but disappear again after April 2019 are likely to have access to private medication coverage through their parent's employers, and hence are more likely to be relatively high income (Barnes and Anderson, 2015). Children who appear in the ODB records after January 2018 and remain after April 2019 are more likely to be those whose income was too high to qualify them for pre-OHIP+ coverage, but whose income was also too low to gain them 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.

This tagging process is complicated by children's age. By construction, children who first appear in the ODB 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 will control for single year of age so that comparisons always involve children of similar age who first appear either pre- or post-OHIP+. However, even conditional on age there will be some unavoidable measurement error in tagging. For example, there will be some low-income children who would have always been eligible for medication coverage but who first appear during the OHIP+ expansion period (and thus get incorrectly classified as "high income") because they did not previously fill prescriptions. And some parents with private medication coverage may have relatively low-wage jobs with a larger employer who offers medication coverage, for example. Hence, while those we tag as low income are accurately identified, those we tag as relatively high-income are so only on average. This means that the low/high-income contrasts we identify are likely to be understated relative to the true income gradients in treatment. Hence, the effects we find should be interpreted as lower bounds on true disparities in treatment.

Our focus is on differences in the types of mental health medications prescribed to children in the three groups. We observe the date the prescription was written and a prescriber identifier.[8] 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 16% of all child ODB patients filled at least one ODB mental health prescription. These children represented 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 these broad medication classes: Attention Deficit-Hyperactivity Disorder (ADHD) medications, antipsychotics, selective serotonin reuptake inhibitors (SSRIs), other antidepressants (including tricyclic antidepressants,

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

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.[9]

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. In addition to the prescriptions, we also have encounter-level data from the main OHIP administrative files on emergency department visits, inpatient hospitalizations, mental health outpatient visits, and cost data for all youth who ever appear in the mental health prescription sample. The coverage period includes all encounters from 365 days before each patient's first observed mental health prescription after Jan. 1 2016, up to the end of 2019. (i.e., there is at least one year of pre-period data for all prescriptions).[10] We observe the dates and the list of diagnosis codes for each encounter. The cost data attributes the expenditures associated with episodes of care and prescriptions using an average cost approach, which is meant to proxy for actual tax-payer costs. Costs are summed across all medical encounters and prescriptions within a 365 day period relative to each childs' first prescription date. Hence, any publicly payed for encounters for covered non-medication mental health treatments are captured in addition to the mental health prescriptions. A limitation of our data is that not all mental health services are covered by OHIP. In particular, while hospital and emergency department visits and all doctor visits are covered, visits to psychologists, counsellors, and social workers who do not have medical degrees are not covered and are not visible in the OHIP administrative data. In other words, we

[9] Because epileptic children need to take anticonvulsants which are also sometimes used as mood stabilizers, we have dropped 2,576 children with epilepsy from our sample.

[10] We actually have data to the end of 2020, but given all the disruptions in care that occurred in 2020, we only use this data to classify children as epileptic or not.

only observe publicly-funded outpatient mental health care by physicians (typically psychiatrists seeing patients referred by general practitioners).

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 at the patient-year level. The table 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. The majority of these prescriptions are for 30 days.

The first two rows of the second panel of Table 1 provide some validation of the tagging procedure described above. Children tagged as "low income" are much less likely to be living in high income, urban postal areas (known as "forward sortation areas" or FSA, corresponding to the first three digits of the postal code).[11] 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. FSAs are large in terms of population (average Ontario FSA has 25,714 people in 2016) and are divided into smaller units called dissemination areas (DAs)—the smallest standard geographic area used by Statistics Canada, which each have about 400 to 700 people and, in urban areas, take up one or more neighboring blocks. In addition to the FSA, we know whether the DA is rural and its income quintile *within* the FSA. This gives us two proxies for residential income, one at a broad FSA-level, and a finer DA-level measure within the FSA. In what follows, we control for

[11] The FSA is indicated by the first three digits of the postal code. There are 513 FSAs in Ontario.

possible area-level contributors to differences between children using these measures, and we focus on within-FSA differences (across DA and across individuals) in prescription patterns.

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. Children in the privately insured group are about a year older on average than children in the other two groups. They are also more likely to be female. These differences will be controlled for in the estimation described below.

Turning to specific 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 had an ADHD medication compared to 50.0 percent of privately insured children. The differences are starker 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). However, turning to antidepressants, low-income children are much less likely to be prescribed antidepressants (32.4 percent) compared to the privately insured (43.1 percent).

In addition, there are large differences in the probability that a child is prescribed two or more different medications in the same month (a measure of polypharmacy). For example, in a typical patient-year, 50.6 percent of low-income children 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.

Table 1 also shows differences in utilization of other types of medical care between the three groups of children. Of these children, who are all taking some type of publicly-funded mental health medication, most receive some additional type of mental health care such as a visit to a psychiatrist. Table 1 shows that the privately insured are slightly less likely than the low income to receive other publicly funded mental health services, which may reflect greater use of private providers such as psychologists. Most (but not all) also have a mental health diagnosis indicated in the records for that patient year. In what follows we control for diagnosis using broad International Classification of Disease codes.[12]

In this population of children using mental health medications, trips to the Emergency department (ED) and hospitalizations for any cause are relatively frequent, with low-income children and those who gained coverage being more likely to use hospital services than the privately insured. Moreover, a large share of these visits include a mental health diagnosis, though the proportion tends to be smaller for the privately insured. Overall, spending for the low-income children is much 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.

An important limitation of our data is that we only see children who ever filled a mental health prescription that was paid for by ODB. However, because all children were covered by ODB in the expansion period (Jan. 1, 2018-March 31, 2019), we can use the full OHIP data from that period to gain insight into the way that mental health treatment, including both medical and pharmaceutical treatment, was delivered in Ontario. We first calculate the fraction of all children who received some form of non-medication treatment for mental health and who also filled a mental health prescription. During the expansion period, this was about 36.6% of all of the

[12] Specifically we include the two most mental health diagnosis ICD codes (at the 3-digit level) in the past year along with indicators for hospitalizations for any reason, hospitalizations for mental health, hospitalizations for injuries, emergency department visit for any reason, emergency department visits for mental health, emergency department visits for injuries, and outpatient mental health visit over the past year (and the same set over the past 30 days).

children receiving publicly paid for mental health treatments other than medications, as shown in Figure 2. We can also see that a further 28,994, or only approximately 14% of children who received a mental health prescription, did not receive any other type of mental health treatment. In total then, approximately 40.2% of children receiving any treatment, medication or non-medication, for a mental health condition filled a prescription.

In addition to the primary patient-year level data set including all children who ever had a prescription for a mental health medication paid for by ODB between Jan. 2016-Dec. 2019, we also construct and analyze a second area-level data set consisting of all encounters for covered mental health care during the expansion period when all Ontario children had medication coverage through ODB. We use this secondary data set to examine variations in mental health care more generally across high and low-income FSAs, and also by dissemination area income levels within FSAs.

IV. Methods

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 first provide a description 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:

$$(1)\ \text{OUTCOME} = \beta_1 \text{FSA}_{top} + \beta_2 \text{FSA}_{bottom} + \varepsilon,$$

where OUTCOME is one of several different measures including the share of children who received any medical mental health care (i.e., care other than mental health prescriptions). This outcome is further broken down into 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 who were prescribed a mental health medication conditional on receiving any mental health care.

FSA_{top} indicates that the child resided in the top quintile of FSAs by income while FSA_{bottom} indicates residence in the bottom quintile of FSAs by income (above \$63,095 and below \$42,286, respectively). These regressions provide a summary description of whether the use of services differs across high- and low-income areas, which could be due to either supply or demand side reasons.

A second set of models take the form:

$$(2)\ \text{OUTCOME} = \beta_1 DA_{top} + \beta_2 DA_{bottom} + \alpha_{FSA} + \varepsilon.$$

These models investigate the same set of outcomes. In these models, each FSA has been split into five groups. DA_{top} represents the highest income small areas within the FSA while DA_{bottom} represents the lowest income small areas within the FSA. α_{FSA} are a set of FSA fixed effects. Importantly, an FSA is small enough in terms of area that people living in urban FSAs have approximately equal geographic access to care.[13] Hence, these models come closer than model (1) to describing how utilization of care varies with family characteristics *conditional* on the fixed characteristics of the local area, such as the locations of hospitals, clinics, and doctors' offices. These regressions are weighted by the FSA population aged 0 to 19, and the standard errors are clustered at the FSA-level.

[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.

In addition to examining the overall receipt of care during the expansion period, we estimate versions of (1) and (2) in which the outcomes are mental health prescriptions broken down by the class of medication. These area-level regressions can then be directly compared to patient-year level models estimated using the main sample of children who received prescriptions covered by ODB anytime between Jan. 1, 2016 and Dec. 31, 2019. Using this, the main sample, we estimate several patient-year-level regressions in which we add categories of variables one at a time. The most fully specified of these models takes the form:

$$(3)\quad OUTCOME_{ift} = \beta_1 LOWINC_{ift} + \beta_2 AGE_{it} + \beta_3 MALE_i + \beta_4 MEDHIST_{it} + \beta_5 DIAGNOSIS_{it} + \beta_6 FSA_f + \beta_7 DOCTOR_{ift} + \varepsilon_{ift},$$

where now the outcomes are the type of medication prescribed; LOWINC indicates that the child participated in ODB prior to the expansion; 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 that includes the two most recent mental health diagnoses the children receive in any observed setting over the past year.

As in (2) we include 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 the same provider is treating high and low income patients who live in the same FSA and have similar diagnoses and medical histories differently in terms of prescriptions of mental health medications. Robust standard errors are clustered at the FSA level.

We have also estimated a version of equation (3) that includes an indicator for the middle-income "gained coverage" group as well as for low-income children. Since the three groups are observed for different lengths of time, for this analysis we construct a sample in which each group of children are followed for 15 months (the length of the expansion period). Also, because we can identify those who gained coverage only if they received a prescription both during the expansion period and after the expansion ended, in this analysis we require all children to have at least two prescriptions. To be included in this analysis, a low-income child must have received at least two prescriptions between Oct. 1, 2016 and Dec. 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.

V. Results

Table 2 presents estimates of equation (1) in Panel A and equation (2) in Panel B for the period of universal ODB access 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. Overall, the means of the dependent variables show that 17.24% of Ontario children are estimated to have received some type of non-medication publicly funded mental health care 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.

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 non-medication mental health care, and that this 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. However, the last column of Panel A shows that conditional on receiving any non-medication mental health services, children in both high- and low-income FSAs are less likely to receive medication prescriptions than children in the middle income FSAs. Although the outcome is the same, the mechanisms could be different if, for example, high income children are more likely to use outpatient therapy, whereas low-income children lack access to providers who could prescribe medication.

As discussed above, equation (2) controls for the local geographic availability of care by including FSA fixed effects. These regressions explore differences in the utilization of care by people who live in high- and low-income areas *within* an FSA. Within FSA, we do not see significant differences in access to any non-medication mental health care, or to outpatient mental health care (such as seeing a psychiatrist), but we do see more reliance on EDs and hospitalizations for mental health care among children in the bottom quintile of income areas within the FSA.   We also see that child residents of higher income parts of the FSA are more likely to fill mental health medication prescriptions than children in middle- or low-income parts of their FSA conditional on receiving any non-medication mental health care. However, the difference is relatively small—2 percentage points on a mean of 39.77, or 5%.

These findings are important because they suggest that within FSAs, differences in the probability of treatment for mental health issues are relatively small, as are differences in the probability of filling any mental health prescriptions conditional on receiving any mental health care. If, within FSA, children are equally likely to be treated for a mental health condition and equally likely to be prescribed some type of psychiatric medication, then it is reasonable to look at differences in what medications they are prescribed as we do in the patient-year level models described below.

Table 3 provides a bridge between the area-level regressions in Table 2 and the patient-year level regressions in subsequent 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 (1) while Panel B shows estimates of equation (2).

Panel A shows that about 8% of Ontario children filled a prescription for a mental health medication during the expansion period. The most common medications filled were ADHD medications (3.98%) and SSRIs (3.52%). 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 2, Panel A of Table 3 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. The most striking difference between high- and low-income FSAs is in the prescription of antipsychotics, where children in high-income FSAs are much less likely to fill a prescription for these medications. However, we also see that children in the lowest income FSAs are significantly less likely than children in high income FSAs to be prescribed ADHD medications as well as mood stabilizers.

Looking within FSA in Panel 3B, reveals a far different pattern. Controlling for area-level differences, we see that children living in higher income parts of the FSA are more likely to be prescribed any psychiatric medications, and this is mainly due to a higher probability of receiving ADHD medications and SSRIs, though there is also a significantly higher probability of receiving benzodiazepines. Children in the lower income parts of the FSA are more likely to be prescribed antipsychotics.

However, the area where one lives is an imperfect proxy for household income. Table 4 presents estimates of equation (3) based on the data on prescriptions at the individual patient-year level. As in Tables 2 and 3, we focus on the expansion period, when all children had equal public drug coverage. 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). Column (2) of Table 4 shows a version of equation (3) that includes only the FSA fixed effects and excludes all other variables. Each column shows the effect of adding additional variables until the last column, column (6) shows the effect of low income in the fully specified model that includes physician fixed effects. Column (2) is most comparable to Table 3 because it includes only FSA fixed effects. Column (2) shows that two of the most striking findings from Table 3 carry over to this patient-year level data: We see that low-income children are less likely to be prescribed SSRIs and more likely to be prescribed antipsychotics. However, unlike Table 3, Table 4 also suggests that low-income children are more likely to be prescribed ADHD medications, benzodiazepines, and mood stabilizers.

Column (3) shows that controlling for the basic demographic characteristics of age and sex has a large impact on the estimated coefficient on low income in the case of ADHD medications, antidepressants, and benzodiazepines. Adding these controls also makes the coefficient on low income become statistically significant in the models for other antidepressants. Remarkably though, in the models for antipsychotics and mood stabilizers, controlling for age and sex has no impact on the estimated coefficient on low income.

Columns (4) and (5) of Table 4 show the impact of adding controls for medical history and diagnoses. This has relatively small impacts in models for most of the medications. For example, the coefficient on low income in the model for antipsychotics falls from 0.166 to 0.146. Adding these controls has a proportionately greater effect on the disparity in SSRI prescriptions, where the coefficient on low income falls from -0.055 to -0.031.

Column (6) shows the impact of adding physician fixed effects. In all cases, the estimates remain statistically significant. For example, the coefficient on low income in the model for antipsychotics falls to 0.133. The stability of these results 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 physician. In other words, the same physician is treating children with similar histories and diagnoses differently.

Panel B of Table 4 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 in the same month. The results indicate that in the fully specified model, low-income children are 31.7% more likely to receive two or more medications, 72.0% more likely to receive three or more medications, and 103% more likely to receive four or more psychiatric medications in a single month. These are effect sizes as a percent of the baseline mean.

In order to assess the robustness of our findings, in Table 5 we present a somewhat different comparison. Table 5 compares children prescribed 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, all of the 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, though it is likely that some new low-income children enter the sample during this period.

Table 5 shows patterns that are very similarly qualitatively, though they are somewhat smaller in magnitude, 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 our analysis so far is that some low-income children have been observed since 2016, so that there is a longer window in which they could have been prescribed a medication. In contrast, the privately insured 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, we estimate a version of (3) that includes indicators for the "gained coverage" group as well as for low income children. This model is estimated on a separate sample as described above in which each type of child is followed for the same length of time (15 months) and all children have at least two prescriptions.

Estimates of the fully specified model (3) with all covariates including the physician fixed effects included are shown in Table 6, with the addition of an indicator equal to one if the child is in the "gained coverage" group. The estimates of the effects of low income are qualitatively similar to those shown in Column (6) of Tables 4 and 5, though the estimated effect of low income on antipsychotic prescriptions is even larger in this specification.

Turning to the new results for the "gained coverage" (middle-income) group, the estimates indicate that they fall between the low-income and the private insurance (high-income) group in the models for antipsychotics, other antidepressants, benzodiazepines, and mood stabilizers. However, they 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.

VI. Discussion and Conclusions

While there is a broad consensus that low-income people receive less appropriate care than richer people conditional on need, the reasons for that difference are controversial. Much of the literature focuses on differences in demand for care which could stem from differences in insurance coverage or in knowledge about appropriate care, or in underlying health needs. Other explanations focus on differences in physical access to care that are reflected in, for example, local shortages of suitable caregivers. This paper provides evidence in support of a third explanation for differences in care, which is that the same providers treat richer and poorer patients differently.

Our study is set in Ontario, a 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 would be expected to 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 children with the same medical history and diagnoses. Estimates of the size of this effect range from 63% to 88% more likely. In Appendix Table 1, we show that if we remove children with any diagnosis of psychosis or conduct disorders from the sample, we still see that doctors are 76% more likely to prescribe antipsychotics to low-income children. This heavy reliance on antipsychotic medications is concerning given that these medications have significant side effects including sedation, weight gain, and metabolic changes that can lead to diabetes and heart disease among others (Stroup and Gray, 2018). In addition, the long-term physical and psychological impacts of the use of these medications in children is not known, and their use in children is not recommended by any professional body for indications other than psychosis and severe conduct disorders[14] (Pathak et al., 2010).

[14] The use of antipsychotics for conduct disorders remains controversial. A 2017 Cochrane review concluded that: "Our analysis suggested that risperidone led to a reduction of aggression (low-quality evidence) and conduct problems (moderate-quality evidence), to some extent, after six weeks of treatment, and that risperidone appeared relatively safe in the short-term. However, it was associated with significant weight gain (low- to moderate-quality evidence). There are other side effects that have not been well studied and long-term effects are not entirely clear. Clinicians prescribing such medication and families need to carefully consider the benefits and risks of medications.

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 physician fixed effects, and they are less likely to be prescribed SSRI's, which are the first-line treatments for anxiety and depression. Appendix Table 1 shows that the increased probability of being prescribed benzodiazepines extends to an increased probability of being prescribed more than once in a 30-day period, which is concerning given that these are addictive drugs and easily abused. Appendix Table 1 also suggests however, that the reduced probability of receiving SSRIs can be protective for the relatively small group of low-income children who have received a diagnosis of bipolar disorder and thus should not receive SSRIs.

Overall, this pattern of results suggests that treatment for low-income children is more likely to focus on quickly altering their behaviors through the use of psychotropic medications than on addressing what may be underlying reasons for that behavior, such as trauma, anxiety or depression. Discrimination or implicit bias on the part of providers may be a factor, but the existence of disparities in treatment does not necessarily prove the existence of such biases because there are many additional possible reasons for disparities (Balsa and McQuire, 2003). For example, low-income children may face more serious consequences of disruptive behaviors (such as being suspended from school), may live in families with less ability to deal with disruptive children (because for example, the parents work long or irregular hours), and they may have less access to therapeutic interventions aimed at addressing these behaviors that are not covered by public health insurance.

There were no studies with children under five years of age. There is a lack of studies of medications other than risperidone" (Loy et al., 2017).

Our results show that this pattern persists even in a setting with universal public health insurance. It is present within small areas where children have similar geographic access to providers. In fact, we show that differences in treatment emerge even among children who see the same doctor and have the same medical histories and diagnoses. 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 fully address disparities in care, and that measures aimed at changing the behaviors of individual providers may also be necessary. Disentangling the reasons for the disparities in treatment, and the effectiveness of potential policy levers are important avenues for future research.

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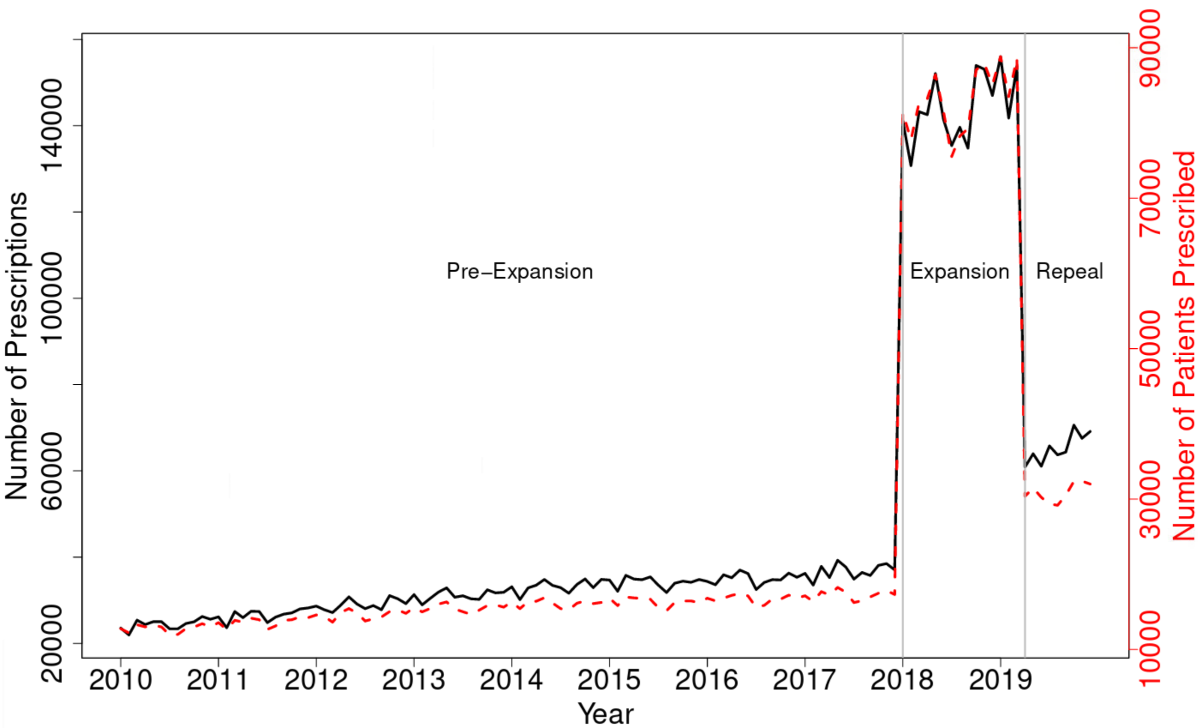
Figure 1. Time Series of Prescriptions and Patients Prescribed Between 2010 and 2019



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: This Venn diagram shows the number of children who are receiving mental health prescriptions or have a mental health diagnosis from hospital or outpatient care ("medical care"). Children with epilepsy are dropped from our sample

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

	Low Income (1)	Privately Insured (2)	Gained Coverage (3)
Patients (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
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	13.70	14.94	13.92
Female	0.410	0.478	0.457
Mental Health prescriptions by Type			
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
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
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)	1,200	778	921

Notes: This table summarizes the analysis sample for January 1, 2016 to December 31, 2019 for each type of patient. Low income patients are those who fill any prescription prior to the OHIP+ expansion period (which began January 1, 2018). Privately insured patients are those who fill a prescription only in the expansion period (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 fill their first prescription in the post-expansion period who make up a fourth category that exhausts the sample. The number of patients and prescriptions, 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: Probability of Receiving Mental Health Care in a Particular Setting in Low Income vs. High Income Postal Areas Under Universal Prescription Coverage, Jan. 2018-March 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:	0.60	0.68	−0.50***	−0.12***	−5.13***
Top quintile	(0.45)	(0.45)	(0.09)	(0.03)	(1.35)
FSA Income:	−0.98**	−1.00**	−0.09	0.04	−7.62***
Bottom quintile	(0.43)	(0.43)	(0.09)	(0.03)	(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:	1.61	1.61	−0.02	−0.01	2.02***
Top quintile	(1.05)	(1.04)	(0.08)	(0.02)	(0.49)
DA Income:	0.12	0.06	0.35***	0.10***	0.77
Bottom quintile	(1.05)	(1.04)	(0.11)	(0.03)	(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 3: Probability of Being Prescribed a Medication in a Particular Class in Low Income vs. High Income Postal Areas Under Universal Child Prescription Drug Coverage, Jan. 2018-March 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.

Table 4: Prescribing to Low Income vs. 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 History	Recent Diagnosis Codes	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.499	0.135***	0.066***	0.064***	0.059***	0.061***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Antipsychotics	0.160	0.164***	0.166***	0.152***	0.146***	0.133***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SSRI	0.438	−0.114***	−0.055***	−0.041***	−0.031***	−0.021***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Other Antidepressants	0.122	0.001	0.020***	0.013***	0.020***	0.020***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Benzodiazepines	0.088	0.013***	0.025***	0.017***	0.024***	0.022***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mood Stabilizers	0.058	0.047***	0.050***	0.037***	0.048***	0.029***
& Anticonvulsants		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

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

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical History	Recent Diagnosis Codes	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.435	0.156***	0.152***	0.139***	0.147***	0.138***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\geq$ 3 drugs	0.154	0.126***	0.127***	0.114***	0.119***	0.111***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\geq$ 4 drugs	0.056	0.068***	0.070***	0.061***	0.064***	0.058***
		(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 drugs (based on Drug Identification Number), excluding opioids, 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 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 5: Prescribing to Low Income vs. Others Based on Pre-Expansion and Universal Child Prescription Drug Coverage, Jan. 2017-March 2019

Panel A. Prescribing of Drug Class

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical History	Recent Diagnosis Codes	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
ADHD	0.486	0.074***	0.015***	0.022***	0.019***	0.017***
		(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Antipsychotics	0.166	0.141***	0.141***	0.128***	0.122***	0.105***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SSRI	0.443	−0.106***	−0.048***	−0.042***	−0.033***	−0.024***
		(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 drugs in a month

		Sequentially Adding Controls:				
	Mean Dep. Var.	FSA	Age & Sex	Prior Medical History	Recent Diagnosis Codes	Physician FE
Low Income	(1)	(2)	(3)	(4)	(5)	(6)
$\geq$ 2 drugs	0.438	0.098***	0.091***	0.081***	0.080***	0.073***
		(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 drugs (based on Drug Identification Number), excluding opioids, 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 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 6: Prescribing by Patient Type During Universal Child Prescription Drug Coverage Jan. 2018-March 2019, Patients with 2+ Prescriptions and Similar Exposure Windows Only

Panel A. Prescribing of Drug Class

	ADHD (1)	Anti-psychotics (2)	SSRI (3)	Other anti-depressant (4)	Benzo-diazepine (5)	Mood stabilizers & anticonvulsants (6)
Low Income	0.037***	0.150***	−0.020***	0.017***	0.023***	0.025***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Gained Coverage	−0.012***	0.043***	0.010***	0.006***	0.008***	0.008***
	(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	0.598	0.295	0.534	0.247	0.236	0.464
N =	171,406	171,406	171,406	171,406	171,406	171,406

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

	Number of Unique Drugs:		
	≥ 2 (1)	≥ 3 (2)	≥ 4 (3)
Low Income	0.115***	0.115***	0.066***
	(0.004)	(0.003)	(0.002)
Gained Coverage	0.033***	0.031***	0.019***
	(0.004)	(0.003)	(0.002)
Mean Dep. Var.	0.499	0.178	0.064
R^2	0.186	0.192	0.166
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 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.

Appendix Table 1: Further Detail About Differential Prescribing of Certain Drug Classes to Low Income Children

Questionable Prescribing to Low Income Based on Pre-Expansion and Expansion Periods

			Sequentially Adding Controls:				
	N	Mean Dep. Var.	FSA	Age & Sex	Prior Medical History	Recent Diagnosis Codes	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***	0.099***	0.082***
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SSRI to bipolar	10,567	0.727	−0.110***	−0.087***	−0.067***	−0.051***	−0.027*
			(0.012)	(0.012)	(0.013)	(0.013)	(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 "questionable prescribing" on whether the patient is low income (following the same definitions and format as Table 5). The "questionable 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 fixed effect for the physician who prescribed them the most frequently. Robust standard errors are clustered at the FSA-level. N=230,683. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Data Appendix: List of drugs in each drug class:

Antipsychotics:
CHLORPROTHIXENE
TRIFLUOPERAZINE HCL
HALOPERIDOL
THIOTHIXENE
PERICIAZINE
METHOTRIMEPRAZINE HCL
CHLORPROMAZINE
CHLORPROMAZINE HCL
PROCHLORPERAZINE MESYLATE
PROCHLORPERAZINE
METHOTRIMEPRAZINE MALEATE
THIOPROPERAZINE MESYLATE
THIORIDAZINE HCL
MESORIDAZINE BESYLATE
PERPHENAZINE
THIOPROPAZATE HCL
FLUPHENAZINE ENANTHATE
FLUPHENAZINE HCL
CHLORMEZANONE
PIMOZIDE
LOXAPINE SUCCINATE
FLUPHENAZINE DECANOATE
LOXAPINE
FLUSPIRILENE
PIPOTIAZINE PALMITATE
FLUPENTIXOL DECANOATE
FLUPENTIXOL HCL
HALOPERIDOL DECANOATE
HALOPERIDOL LACTATE
CLOZAPINE
METHOTRIMEPRAZINE
RISPERIDONE
FLUPENTIXOL DIHYDROCHLORIDE
FLUPENTIXOL
ZUCLOPENTHIXOL HCL
ZUCLOPENTHIXOL DECANOATE
OLANZAPINE
ZUCLOPENTHIXOL ACETATE
QUETIAPINE FUMARATE
LOXAPINE HCL
ZIPRASIDONE HCL
PALIPERIDONE
ARIPIPRAZOLE

QUETIAPINE
PALIPERIDONE PALMITATE
ASENAPINE
LURASIDONE HCL
RISPERIDONE TARTRATE
AMISULPRIDE

ADHD:
METHYLPHENIDATE HCL
DEXTROAMPHETAMINE SULFATE
DIETHYLPROPION HCL
PEMOLINE
FENFLURAMINE HCL
MAZINDOL
PHENTERMINE HCL
DEXTROAMPHETAMINE
DEXFENFLURAMINE
MODAFINIL
AMPHETAMINE ASPARTATE & AMPHETAMINE SULFATE & DEXTROAMPHETAMINE SACCHARATE & DEXTROAMPHETAMINE SULFATE
ATOMOXETINE HCL
ATOMOXETINE
METHYLPHENIDATE
LISDEXAMFETAMINE DIMESILATE

SSRI:
FLUOXETINE HCL
FLUVOXAMINE MALEATE
PAROXETINE HCL
SERTRALINE HCL
FLUOXETINE
SERTRALINE
CITALOPRAM HBR
FLUVOXAMINE
ESCITALOPRAM OXALATE

Other Antidepressants:
TRYPTOPHAN
TRAZODONE HCL
BUPROPION HCL
MIRTAZAPINE
NEFAZODONE HCL
VENLAFAXINE HCL
DULOXETINE
DULOXETINE HCL

DESIPRAMINE HCL
IMIPRAMINE HCL
ISOCARBOXAZID
NORTRIPTYLINE HCL
AMITRIPTYLINE
AMITRIPTYLINE HCL
DOXEPIN HCL
TRIMIPRAMINE MALEATE
TRANYLCYPROMINE SULFATE
AMITRIPTYLINE HCL & PERPHENAZINE
PROTRIPTYLINE HCL
CLOMIPRAMINE HCL
PHENELZINE SULFATE
AMOXAPINE
CYCLOBENZAPRINE HCL
MOCLOBEMIDE
TRIMIPRAMINE
CLOMIPRAMINE
NORTRIPTYLINE

Benzodiazepines:
ZOPICLONE
IVABRADINE HCL
MIDAZOLAM HCL

Opioid Analgesics:
CODEINE PHOSPHATE
ANILERIDINE HCL
PROPOXYPHENE HCL
LEVORPHANOL TARTRATE
MEPERIDINE HCL
OPIUM
HYDROMORPHONE
HYDROMORPHONE HCL
DEXTROPROPOXYPHENE HCL
DEXTROPROPOXYPHENE NAPSYLATE
ACETAMINOPHEN & CAFFEINE CITRATE & CODEINE PHOSPHATE
MORPHINE SULFATE
OXYCODONE HCL
ACETAMINOPHEN & CAFFEINE & CODEINE PHOSPHATE
BELLADONA EXTRACT FOR ORAL USE & OPIUM POWDER
MORPHINE HCL
ACETAMINOPHEN & OXYCODONE HCL
ACETYLSALICYLIC ACID & OXYCODONE HCL
OXYMORPHONE HCL
ACETAMINOPHEN & CODEINE PHOSPHATE

MORPHINE
BELLADONA & OPIUM
FENTANYL CITRATE
SUFENTANIL CITRATE
HYDROMORPHONE HBR
CODEINE SULFATE
FENTANYL

Mood-Stabilizers and Anticonvulsants:
CARBAMAZEPINE
MAGNESIUM SULFATE
VALPROIC ACID SODIUM
DIVALPROEX SODIUM
MAGNESIUM
VALPROIC ACID
LAMOTRIGINE
TOPIRAMATE
DIVALPROEX
OXCARBAZEPINE
LEVETIRACETAM
PREGABALIN
LACOSAMIDE HCL
RUFINAMIDE
STIRIPENTOL
PERAMPANEL
ESLICARBAZEPINE ACETATE
BRIVARACETAM
LACOSAMIDE
ZONISAMIDE