Cash Welfare and Health Spending

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Abstract

I explore the interplay between cash welfare programs and health using Canadian administrative data. Health spending doubles before a welfare application, then partially returns to normal levels within three years. Using quasi-experimental variation in application adjudicators, I estimate that welfare receipt has, at most, minor positive effects on universally insured healthcare use. These findings imply that welfare insures against health risk without significantly affecting health outcomes. Welfare does substantially increase pharmaceutical use, which is not universally insured but for which welfare recipients are subsidized, implying that incomplete drug insurance strongly limits medication access among low-income households that cannot access welfare.

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Health and social policy are closely linked. Poor health can impair a person's ability to work and maintain their income (e.g., Dobkin et al. (2018); Stepner (2019)), which is the rationale for programs such as disability insurance and workplace injury compensation. Even transfer programs that do not require ill health for eligibility, such as cash welfare, may insure against health-related income losses which are otherwise uninsured. Furthermore, economists and public health experts often argue that social policies directly impact health by changing financial resources and precarity, stress levels, and time use (e.g., Herd and Moynihan (2020); The Lancet (2020)). I examine these interactions for a traditional cash welfare system: to what degree does welfare insure health risk, and does access to welfare affect subsequent health outcomes?

My context is the Income Assistance (IA) program in British Columbia, Canada. It offers subsistence-level cash transfers to very low-income households, regardless of their health status, often conditional on searching for work, with compliance overseen by case workers. There are separate programs explicitly designed to cover health-related nonemployment.[1] Along these dimensions, IA closely resembles welfare programs in other developed countries. Canada is advantageous for this research since most healthcare runs through the public system, allowing me to use a novel linkage of administrative IA records and almost all medical spending data, including hospital admissions, outpatient care, and pharmaceuticals.

Consistent with the notion that welfare insures health risk, hospital and outpatient spending among welfare applicants doubles in the months before application. These spending spikes appear in diagnostic categories that could represent impediments to work, such as mental health and physical injury, and are relatively temporary, as spending partially reverts to baseline levels within three years. These patterns suggest that welfare insures against short-term health shocks that may be uninsured through other programs. Health spending does not spike for minor ailments such as respiratory illnesses, nor does it spike for the children of adult applicants, both of which suggest that pre-application health spending is not driven by sudden changes in time availability.

Describing the system in these terms emphasizes the importance of studying the interactions between welfare and health together rather than as two distinct issues. An integral part of this relationship is whether welfare directly affects health. Such effects would be important on their

[1] These include disability insurance (DI), workplace injury compensation, and short-term sickness benefits embedded in the unemployment insurance system. DI benefits are offered under the same heading as "Income Assistance", but the DI benefits are largely excluded in this paper.

own and could affect recipients' long-term reliance on transfer programs.

To obtain causal estimates, I use quasi-experimental variation in the approval propensity of application adjudicators. During the sample period (1997-2005), applications were submitted at local field offices and adjudicated by officers in the respective office. I show that the assignment of applicants to adjudicators is effectively random within an office and that there is considerable variance in the leniency of adjudicators. These conditions allow the use of adjudicator assignment as an instrumental variable for application approval.

I first estimate whether application approval implies just short-term differences in IA receipt, or persistent long-term differences, relative to denied applicants. Approval causes 5.67 months of benefit receipt in the three years after application, relative to initially-denied applicants, which translates to \$5,750 in 2022 CAD (\$3,958 in 2002 CAD). However, by the third year after the application, there is no difference between initially approved and denied applicants. This is consistent with Green and Warburton (2004)'s finding that most approved applicants eventually exit IA, but small and equal-sized subsets of both approved and denied applicants use IA 3 to 5 years later. Benefits are time-unlimited, so exits from IA are voluntary rather than forced.

Next, I examine the effects of approval on universally-insured hospital and outpatient costs. I find statistically insignificant small positive effects in the three years following application, ruling out effect sizes greater than 0.236 and smaller than -0.116 standard deviations with 95% confidence. Translated to dollar terms, every dollar paid by welfare is associated with a 7.5-cent increase in health costs. These effects are nearly statistically significant in the first post-application year, which is consistent with welfare recipients having more time available to seek healthcare and/or being connected with healthcare resources through welfare case workers. I fail to find effects on mortality or fertility, although these outcomes are underpowered.

There are, however, increases in pharmaceutical spending and physician visits associated with pharmaceutical prescribing. Drug spending in the three years after application increases by \$408, or 0.20 standard deviations, with 40% of this effect driven by mental health-related treatment. Unlike hospital and outpatient costs, pharmaceuticals are not universally-insured, but welfare recipients receive much larger government pharmaceutical subsidies than non-recipients. If welfare affects drug spending solely through the subsidy, the implied price elasticity is -1.6, which is higher than found in other contexts (Goldman, Joyce and Zheng, 2007) as discussed in section 4.4.

The majority of my analysis sample is childless adults. Motivated by the fact that childless adults are ineligible for welfare (Temporary Assistance for Needy Families (TANF)) in the US, but are eligible in Canada and some European countries, I estimate effects for each demographic.[2] Both show strong increases in pharmaceutical use, but mixed results for hospital and outpatient care. Parents (mostly mothers) are more likely to see increases in treatment for physical injury, while childless adults (mostly men) are more likely to see increased mental health treatment. Explanations for these patterns are discussed in section 4.5.

My first contribution is documenting that many welfare applicants experience health shocks before applying for assistance. This suggests that cash welfare insures health risks even in the presence of separate sickness insurance, disability insurance, and workplace injury compensation programs designed to cover health shocks. This is important, in part, because government transfers tend to be more valued in states of poor health.[3] And it mirrors findings that disability insurance, which is intended to cover *health* risk, also insures a substantial degree of *nonhealth* risk (Deshpande, Gross and Su, 2021; Deshpande and Lockwood, 2022). Both cash welfare and disability insurance, are, in fact, offering some degree of overlapping insurance.[4]

My second contribution comes from the causal identification of welfare access on health outcomes. In a review article, Shahidi et al. (2019) surveyed 17 papers from developed countries documenting the association between health and welfare programs. Thirteen of those papers are descriptive, such as comparing recipients to non-recipients. Of the remaining four that use quasi-experimental variation, two study whether small-scale welfare-to-work experiments in Florida and Connecticut affected long-term mortality (Muennig, Rosen and Wilde, 2013; Wilde et al., 2014). Both studies have low statistical power and fail to find effects on mortality.[5] The remaining studies use the 1990s US welfare reforms (Basu et al., 2016; Narain et al., 2017).

Studies of US reform illustrate two more contributions. First, those studies use survey-based

[2]Coverage of childless adults under other safety net programs such as the EITC and SNAP are active policy debates in the US (Carlson, Rosenbaum and Keith-Jennings, 2016; Crandall-Hollick, 2021; Meer and Witter, 2022).

[3]See, for example, Low and Pistaferri (2015) who estimate a life-cycle model of labor supply and health risk, finding that poor health raises both the fixed cost of work and the marginal utility of consumption and lowers wages.

[4]Relatedly, by linking survey data on transfer programs to medical records from the US Department of Veterans Affairs (VA), Wu and Zhang (2022) document that health worsens before enrollment in VA Disability Benefits.

[5]Both experiments imposed time limits, job search, and training requirements on welfare recipients. The experiments had small sample sizes (about 2000 per group) and long-term mortality rates of 4%-5%, which limits statistical power. Neither finds statistically significant effects (Muennig, Rosen and Wilde (2013)'s original result did, but the errata corrects this). Low power is a common issue in social policy experiments (Courtin et al., 2020).

self-reports of healthiness (Kaestner and Tarlov, 2006; Basu et al., 2016; Narain et al., 2017).[6] Self-reports may both contain measurement error (Baker, Stabile and Deri, 2004) and cause biased estimates if receiving welfare changes one's perception of their health (Currie and Madrian, 1999). My administrative data are free of measurement error and contain breakdowns of spending across diagnostic categories. Using health care does mean that I study effects on health care utilization rather than underlying health. Section 4 discusses mechanisms underpinning effects on health care utilization. Second, US reform reduced health insurance coverage as some low-income households were disenrolled from Medicaid without gaining employer-sponsored insurance (Garrett and Holahan, 2000; Kaestner and Kaushal, 2003; Bitler, Gelbach and Hoynes, 2005; Cawley, Schroeder and Simon, 2006). As a result, any observed relation between welfare and self-reported health may reflect changes in insurance coverage. Indeed, Finkelstein et al. (2012) show increases in both self-reported well-being and health spending due to Medicaid enrollment. Health insurance in Canada is nearly universal regardless of welfare status, which allows me to sidestep confounding insurance changes. Illustrating the importance of this insurance mechanism, the strongest causal effect that I find is on drug spending, the one domain in which welfare access does affect health insurance.

Overall, I conclude that cash welfare provides a certain degree of income-replacement insurance against health shocks without inducing large spillovers into healthcare costs. My causal identification only considers people on the margin of receiving assistance, and consequently, the results should not be generalized to all recipients. The large effect on pharmaceuticals, driven by subsidies available to welfare recipients, suggests that incomplete insurance coverage is holding back medication access among low-income households that cannot access welfare. Such households also face barriers to accessing other non-insured medical expenses, notably dental care. My results, therefore, also inform proposals to expand means-tested insurance for dental care and drugs (*e.g.*, Green, Rhys and Tedds (2021); Robson, Schirle and Lindsay (2022); Health Canada (2019)).

The paper proceeds as follows. Section 1 outlines the institutional background. Section 2 describes the data. Section 3 examines trends in health spending around the time of application. Section 4 contains the causal analysis of benefit approval on health outcomes. Section 5 concludes.

[6] The exceptions are Kaestner and Lee (2005) and Leonard and Mas (2008) who study infant mortality and birth weight. In the DI literature, Black et al. (2018) and Gelber and Strand (2023) estimate the effect of DI on mortality; Black et al. (2018) find that access to DI raises mortality, while Gelber and Strand (2023) find that, conditional on access, higher benefit amounts lower mortality. Silver and Zhang (2022) find that variation in DI benefit amounts has limited effect on health spending and self-reported health for US military veterans that have a mental health diagnosis.

1 Institutional Details

1.1 Overview of the British Columbia (BC) Income Assistance (IA) System

BC's IA system is the primary income support program available to low-income and low-asset individuals who do not qualify for other government support, such as UI benefits and workplace injury compensation. The program broadly classifies clients into those with work-limiting disabilities and those without them. Benefits are largest for persons with disabilities, but the application requirements are more arduous, including having to receive a medical designation of disability. Persons deemed employable constituted the large majority of IA recipients during my sample period and are the focus of this study. I refer to IA for “employables" as “welfare" because the program structure is similar to welfare programs elsewhere (such as TANF). The following program details are specifically for welfare during my period of study (1997-2005).

Eligibility: Eligible households must have sufficiently low income, sufficiently few assets, and reside in the province. *Eligibility is not dependent on health status.* Before 2002, recipients could earn \$100 per month before a dollar-for-dollar claw-back of benefits took effect. If a household's income was sufficient to fully claw-back the IA benefit, they are ineligible. The \$100 exemption was reduced to \$0 in 2002. Assets primarily refer to cash and investments given the long list of other assets that are exempted, including one's residence and one vehicle. In 2002, eligible single adult and multi-adult households could have a maximum of \$1,500 and \$2,500 in non-exempted assets, respectively.

Benefits: Benefits increase with the number of people in the household, both children and adults. Benefit rates were stable during the sample period of this study (1997-2005; see Figure B.1). Average monthly benefits in 2002 were approximately \$500 (CAD) for childless adults and \$900 for families with children, or \$6,000 and \$11,000 annually. In comparison, the 10th percentile of household income in 2002 was \$12,400[7], which highlights that welfare was a last resort rather than a desirable long-term option. Benefits are time-unlimited.

Requirements and Compliance: IA recipients are required to self-report all income on a monthly basis and search for and accept work (except for mothers with young children).[8] Case

[7] Source: https://www150.statcan.gc.ca/n1/en/daily-quotidien/151217/dq151217c-eng.pdf?st=xBocgdx

[8] Mothers were exempt from the work search requirement if their youngest child was less than a certain age: age

workers ("Financial Assistance Workers") monitored recipients to ensure compliance with these obligations. Case workers were also responsible for ensuring that recipients were aware of other services available to them, such as filing tax returns to obtain refundable tax credits.

Reform in 2002: The system underwent reform in 2002, causing the caseload to decline from 9% of the population in 1999 to 5% in 2005 (see Green et al. (2021); Kneebone and White (2009) for overviews). This reform expanded work search requirements for mothers with young children, imposed a three-week waiting period between application and benefit receipt, and required applicants to demonstrate financial independence in each of the two years before the application.[9]

1.2 Application Process and The Early Detection Program

Spurred by rising caseloads in the 1990s, the Early Detection Program (EDP) was established in 1996 to detect "errors" in the determination of applicants' eligibility.[10] My causal identification strategy leverages a feature of the EDP, namely, Verification Officers.

At the time, eligibility was evaluated at field offices where applicants applied. The EDP instituted a new staffing position in these offices called Verification Officers (VOs). Under this system, an Intake Officer would conduct an initial assessment of an application, after which they could approve, deny, or refer the application to a VO for further examination. Upon referral, the VO would investigate applicants' eligibility, including specific concerns raised by the Intake Officer, then make a recommendation on whether to approve the application, typically within 5 business days. The Intake Officer then made the final decision — they followed the VO's recommendation in 70% of cases. I use "VO" and "adjudicator" synonymously.

Applications Reviewed: As the program launched in 1996 and 1997, fewer than 20% of applicants were reviewed (see Figure B.2). By 2000, approximately 40% were reviewed. The EDP ended in 2006 when the application system moved towards centralized telephone and internet platforms. Formal criteria outlined which applications an Intake Officer should refer to a VO, which largely centered on three common concerns about eligibility: undeclared income, undeclared as-

12 before 1996, age 7 from 1996 to 2002, and age 3 from 2002 onward.

[9]Financial independence was defined as having $7,000 in own-income in each year. This measure was intended to stop young adults from exiting high school and immediately entering IA.

[10]Highlighting the focus on enforcement of mistakes or fraudulent reporting by applicants, the inaugural head of the EDP was a retired police officer. More generally, training manuals indicate that one measure of the program's success was the number of "diverted" applications (Ministry of Human Resources, 1997*a*).

sets, and unreported supporting spouses (Ministry of Human Resources, 1997*a*).

Discretion: VOs had opportunities for discretion in determining what evidentiary standard to apply and how to interpret that evidence. For example, VOs had regulatory authority to pursue a range of investigative procedures, including requiring additional documentation[11], conducting interviews with applicants, contacting neighbors and past employers, arranging in-home visits, and performing street surveillance (Ministry of Human Resources, 1997*a*), while training manuals provided instruction on interpreting body language during interviews as signs of potentially fraudulent behavior.[12] At the end of the investigation, VOs only provided verbal reasons for the denial to applicants. These opportunities for discretion in the application system were the basis for an Ombudsperson's recommendation for a more accessible appeals process (Ombudsperson BC, 2006). Footnote 13 describes the appeals process.[13]

VO Assignment: The VO who was working and available at the time of referral would receive the application. VOs did not specialize in particular types of applicants, nor could applicants control which VO reviewed their application (Ministry of Human Resources, 1997*a*). As a result, the assignment of applications to VOs was plausibly random within a field office. Supporting evidence for random assignment is provided in section 4.

1.3 Health Care

Most health care in Canada is universally insured. The key exceptions are pharmaceuticals, dental care, vision, some medical devices, and non-medically necessary services such as massage therapy. IA recipients receive larger subsidies than low-income non-recipients for some of these uninsured treatments, most prominently a 100% subsidy for pharmaceuticals. The analysis below separates universally insured medical spending (hospital and outpatient) from pharmaceutical spending and

[11] Such as bank statements, employer tax slips, utility bills, notices of delinquency, tenancy agreements, letters from landlords proving missed rent checks, and so forth.

[12] For example: "Smiling is the most misleading of gestures. Most liars know enough to smile in order to cover up an unpleasant situation.", "When a woman spreads her hands across her chest, she may be lying.", and "If a lot of leg activity is occurring, discomfort and deception may be indicated"(p.88-90 of Ministry of Human Resources (1997*a*)).

[13] A denied applicant had 20 business days to request a reconsideration. If the reconsideration upholds the original decision, the applicant had 7 business days to request a hearing with the Employment and Assistance Appeal Tribunal, which is an arms-length body. At each of these steps, the applicant can provide additional information pertaining to eligibility. Before 2006, the IA Ministry maintained that cases were not eligible for reconsideration if the decision made by the ministry was deemed "automatic" on the basis of legislation, although a 2006 Ombudsperson report argued that reconsideration should be available to everyone (Ombudsperson BC, 2006) due to the limited extent of "automatic" decisions. And practically speaking, multiple Ombudsperson reports argue that Ministry staff did not consistently inform applicants of their rights to appeal (Ombudsperson BC, 2006; Ronayne et al., 2009).

directly estimates the causal effect of IA receipt on net-of-subsidy drug prices facing individuals. See footnote 14 for additional details on supplemental insurance programs.[14]

Treatment for mental health is considered in section 4 because mental illnesses are prevalent among IA recipients (Green et al., 2021). Mental health treatment through family physicians and psychiatrists is universally insured. Both can prescribe pharmaceuticals, and the latter can offer dedicated counseling. Treatment from psychologists and counselors is typically not covered unless these services are delivered in the hospital setting or in dedicated mental health facilities.[15]

2 Data and Sample Selection

IA Data: I access all applications for approved and denied applicants between 1995 and 2005. Because families apply jointly for IA, all adults listed on the application are considered applicants. Nonetheless, the large majority of applicants are sole-headed households.[16] Construction of the application data is described in Appendix A.1. I observe which office processed the application, whether the application was reviewed by a VO, and if so, an identifier for the VO. For approved applicants, monthly payment amounts and program classification are observed (people with disabilities versus employable).

Health Data: The first data set is all payments made to physicians under the provincial univer-

[14] Before 2002, only IA recipients and seniors received pharmaceutical subsidies, except in catastrophic circumstances. After 2002, non-senior, non-IA recipients received public coverage, but with a copay of 30% and a deductible that scaled with household income, from $0 for families with income less than $15,000, 2% of gross family income if income between $15,000 and $30,000, and 4% of family income if income greater than $40,000. Hanley et al. (2008) report that the extension of coverage to this group had very little effect on the out-of-pocket expenses of non-IA households, presumably due to most pharmaceutical needs not exceeding the deductible. “Plan F" of the provincial Pharmacare provides 100% cost coverage for psychiatric medications for clients of provincial Mental Health Centers for a limited time. Drugs delivered in a hospital inpatient setting are universally-insured. Finally, First Nations and Inuit persons receive government supplemental insurance for drugs, dental, vision, and some medical devices under Health Canada’s First Nations and Inuit Supplementary Health Benefits. Government dental care coverage for the broader population is outlined in Table 9 in the following document: https://web.archive.org/web/20220121012153/https://www.caphd.ca/sites/default/files/Environmental_Scan.pdf. Adult IA recipients that are considered employable do not receive coverage, but those considered to have persistent barriers to work receive partial coverage. Children from low-income households, in theory, received the same dental coverage under the *Healthy Kids* program regardless of whether their parents received IA. In practice, there is imperfect take-up of Healthy Kids coverage among eligible families. BC’s pharmaceutical coverage during my sample period is discussed in Hanley et al. (2008).

[15] Most communities in the province have dedicated “Mental Health Teams" that provide mental health services (free of charge) in a team-based setting that includes psychiatrists, counselors, social workers, and consulting family physicians. Source: https://cmha.bc.ca/documents/getting-help-for-mental-illnesses-2/

[16] Approximately 15% of applicants in the sample are dual-headed households, based on self-reported family status at the time of application.

sal health insurance plan, the Medical Insurance Plan (MSP). The second data set is the Discharge Abstract Database, which contains all hospital inpatient visits and day surgeries performed in a hospital. For each outpatient and hospital record, I observe the associated cost.[17] See Appendix A.2 for details of hospital costing. The main exclusions from these combined data are non-medically necessary dental, vision, and allied health services (e.g., chiropractors).[18] The hospital data do not include emergency department visits unless they result in hospital admission. However, emergency department visits will appear in the MSP data if a non-hospitalist performs the treatment. The third data set is Pharmanet, the provincial tracking system for prescriptions filled in community pharmacies.[19] It includes the prescription cost and the AHFS Pharmacologic-Therapeutic Classification code. These three data sets jointly cover the majority of health spending.[20]

Using diagnostic codes from hospital and physician spending, I construct measures of total spending for physical injuries, mental health, and respiratory illnesses.[21] I also measure visits to general practitioners (GPs) who are a primary gateway to health care in Canada.[22] Using the AHFS code, I create an indicator for drugs that are typically prescribed for mental health treatment.[23]

Proxy for Employment: The public health insurance program (MSP) is funded by household premiums. In some cases, an employer will pay the premiums on behalf of its employees. I observe when this happens and use it as a proxy for employment. This proxy considerably undercounts employment by excluding employed individuals who pay their own premiums. Because premiums are typically paid at the household level, if one adult has premiums paid by an employer, then other adults in the household may appear to be employed, leading to an over-count for multi-adult families. I use this employment proxy cautiously.

[17] There is no distinction between "list" and "billed" prices as in the US.

[18] I exclude hospital inpatient admissions due to pregnancies.

[19] Pharmanet excludes prescriptions filled at hospital pharmacies, mental health centers, and the BC Cancer Agency.

[20] Hospital, physicians, and insured drugs make up approximately 70% of government health spending (excluding capital expenses). Source: https://www.cihi.ca/en/national-health-expenditure-trends

[21] Physical injuries are ICD9 diagnostic codes ranging from 800 to 900 (injuries and poisonings). Respiratory illness is ICD9 codes 461 to 466 and 480 to 488. Mental health treatment is ICD9 codes 290 to 319. A complete listing of ICD9 codes is available here: https://www2.gov.bc.ca/gov/content/health/practitioner-professional-resources/msp/physicians/diagnostic-code-descriptions-icd-9

[22] GP visits are identified by MSP fee codes 12101, 00101, 15301, 16101, 17101, 18101, 12201, 13201,15201, 16201, 17201, 18201, 12100, 00100, 15300, 16100, 17100, 18100, 12200, 13200,15200, 16200, 17200, 18200. Descriptions of each are here: https://www2.gov.bc.ca/assets/gov/health/practitioner-pro/medical-services-plan/msc-payment-schedule-december-2016.pdf

[23] AHFS4 codes Anticonvulsants (28:12) (used for personality disorder treatment), Psycho-therapeutic Agents (28:16), Anti-manic Agents (28:28), Opiate Antagonists (28:10).

Inferring Parental Status: I infer that an applicant is a parent if any of the following are true: (a) they were linked to a child on the MSP premiums registration; (b) they applied for IA while listing a child present in the home; (c) they appeared in the birth records as parents of a child born in the past 19 years. As a result, some adults will be classified as parents despite not living with the child.

2.1 Sample Descriptives

I focus on adult applicants (ages 19 to 60) between 1997 and 2005.[24] Table 1 shows their demographics at the time of the application and average health outcomes during the 12 months before the application. The traits of all applicants are compared to the subset that was reviewed by a VO to understand the selection into the VO review.

Of the 507,731 applications, 156,819 were reviewed. These 156,819 applications were made by 118,476 unique applicants. There are fewer applicants than applications because some people applied multiple times between 1997 and 2005. The application approval rate is 60% in the full sample and 76% in the VO-reviewed sample. The full sample includes applications that were abandoned by the applicant, which lowers the approval rate, whereas only fully complete applications are eligible for VO review, thus raising the approval rate in that sub-sample.

Two aspects of the composition of applicants stand out. First, most are childless: 57.4% of all applicants and 51.6% of those reviewed by a VO. Second, 66%-78% of applicants had received IA at some point before the application. This reflects the widespread use of IA in the 1990s (Green et al., 2021). Finally, 3% of applicants died within four years of applying. In the analysis below, I drop person-year observations in which the applicant is deceased.

3 Trends Around the Time of Application

Examining trends in health around application for welfare serves multiple purposes. The nature of health degradation prior to application characterizes what shocks IA is effectively insuring. Post-application trends indicate how persistent the shocks are.

In Figures 1 to 3, I plot the monthly average of each outcome from 12 months before the application to 36 months after, separately for approved and denied applicants. Panel (a) of Figure

[24] Those older than 60 are near retirement age, which would see them move off IA and onto retirement benefits. People under 19 years of age will usually be under the care of their parents. The sample of children linked to their parents' applications is small, but I do show trends in children's health spending around application in section B.6.

Table 1: **Application Descriptive Statistics by Approval Status**

	All Applications				Reviewed Applications			
	All	$D = 1$	$D = 0$	ρ	All	$D = 1$	$D = 0$	ρ
Approved	0.6	1	0		0.76	1	0	
Parent	0.43	0.43	0.42	0	0.48	0.49	0.48	0.08
Female	0.45	0.45	0.45	0.03	0.44	0.44	0.43	0
Age	34.42	34.47	34.34	0	34.96	34.91	35.12	0
No Income Assistance (IA) History	0.33	0.25	0.46	0	0.23	0.2	0.31	0
Employer Paid Insurance Premiums	0.18	0.15	0.23	0	0.12	0.11	0.14	0
Any Medical Care	0.72	0.71	0.73	0	0.72	0.71	0.74	0
Treated in Hospital	0.11	0.11	0.11	0	0.12	0.12	0.12	0.02
Hospital and Outpatient Spending	1005.44	949.66	1089.82	0	1048.3	992.6	1224.94	0
Visited GP	0.67	0.66	0.68	0	0.66	0.66	0.69	0
GP Visits Spending	115.97	115.22	117.1	0	124.98	123.86	128.52	0
Treated for Injury	0.23	0.24	0.23	0	0.26	0.26	0.27	0
Injury Spending	29.68	29.64	29.74	0.83	34.91	34.3	36.84	0.02
Treated for Respiratory Illness	0.18	0.17	0.18	0	0.18	0.17	0.18	0
Respiratory Illness Spending	9.1	9.01	9.24	0.05	9.15	9	9.64	0.07
Treated for Mental Health (MH)	0.27	0.27	0.26	0	0.3	0.3	0.3	0.19
Mental Health Spending	77.99	77.43	78.85	0.17	86.64	83.35	97.09	0
Received Pharmaceuticals	0.56	0.55	0.57	0	0.63	0.63	0.63	0.01
Pharmaceutical Spending	194.88	188.66	204.28	0	200.87	193.94	222.84	0
Share Drug Cost Uninsured	0.76	0.7	0.84	0	0.66	0.65	0.71	0
Received MH Pharmaceuticals	0.2	0.2	0.2	0	0.25	0.25	0.24	0
MH Pharmaceutical Spending	66.49	65.55	67.92	0.01	66.92	65.12	72.62	0
4-Year Mortality Rate	0.02	0.02	0.02	0	0.03	0.03	0.03	0.55
# of unique adult applicants	321167	208593	165233		118476	96102	32922	
# of adult applications	507731	305682	202049		156819	119224	37595	

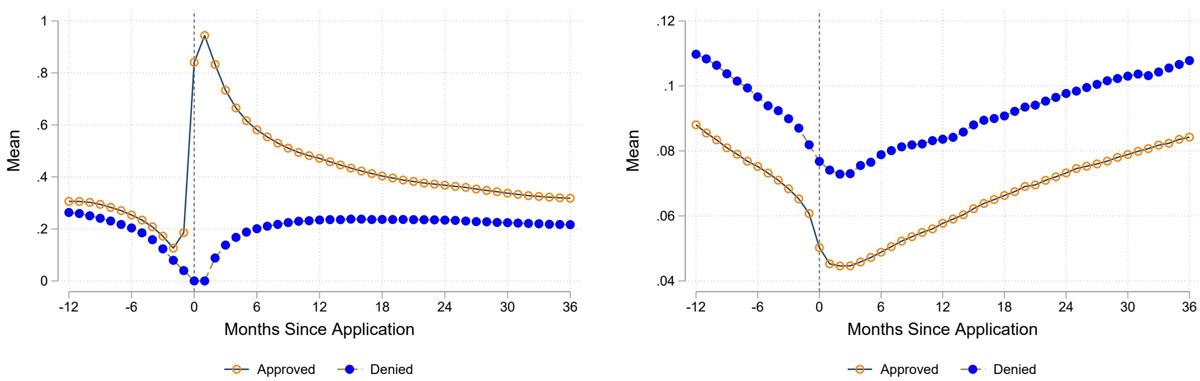
Note: This table contains mean pre-application characteristics for all applicant-application pairs from 1997 to 2005 and the subset of applications that were reviewed by a VO. There are fewer applicants than applications because some people applied multiple times between 1997 and 2005. Similarly, the number of approved *applicants* and denied *applicants* is greater than the total number of *applicants* because some of those who applied twice had different approval decisions across applications. Averages are also shown separately for approved and denied applicants — ρ is the p-value testing the difference of means between the two. Health spending is measured cumulatively over the 12 months before application. Dollar values are in 2002 CAD and winsorized at the 99th percentile.

1 starts with welfare receipt itself. Approximately 1/3rd of applicants received IA in the 12 months before their application, which reflects the large number of users who frequently transitioned on and off assistance during this time (Green et al., 2021). By definition, denied applicants do not receive IA in the month of application, but 23% of these applicants reapplied and received benefits over the following 12 months. Only 31% of approved applicants received benefits 36 months after the application, implying that IA is a temporary support for most applicants. Among that 31%, about one-fourth had transitioned to disability benefits, and one-fifth had transitioned to categories that exempt work search requirements (see Figure B.3).

Trends in the employment proxy are shown in panel (b). Approved applicants show a gradual 3.8 p.p. (38%) decrease in employment prior to application. Denied applicants exhibit a similar downward trend but have approximately 35% higher baseline employment than approved applicants. Both return to their baseline employment rates within 3 years, suggesting that there is no long-term employment displacement. However, the most salient observation is the very low employment levels before application, suggesting that the employment proxy substantially undercounts true employment.

Figure 1: **Welfare Receipt Around Application for IA**

(a) **IA Use** (b) **Employer Paid Premiums**



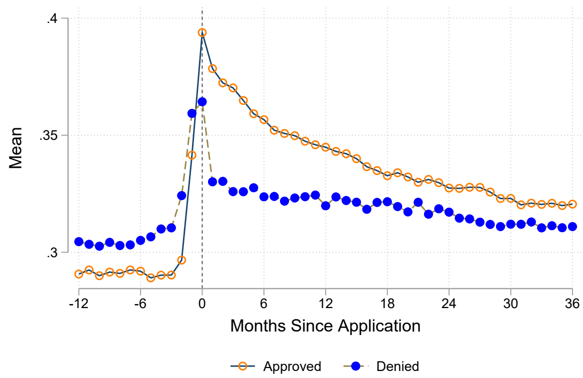
Note: The fraction of applicants receiving welfare (panel (a)) and the fraction who had their health insurance premiums paid by an employer (panel(b)) are plotted for each month around the time of application ($t = 0$) among the set of VO-reviewed applications, separately for approved and denied applicants.

Trends in health outcomes are shown in Figure 2. As shown in panel (a), the monthly probability of receiving outpatient or hospital medical care increases from 29% to 39% among approved applicants and from 31% to 36% among denied applicants. The corresponding spending doubles from $45 to $85. Spending peaks in the month before application and then reverts downward to near-baseline levels within a few years. It seems that the culmination of health shocks prompts an application for assistance, while these shocks are somewhat temporary.

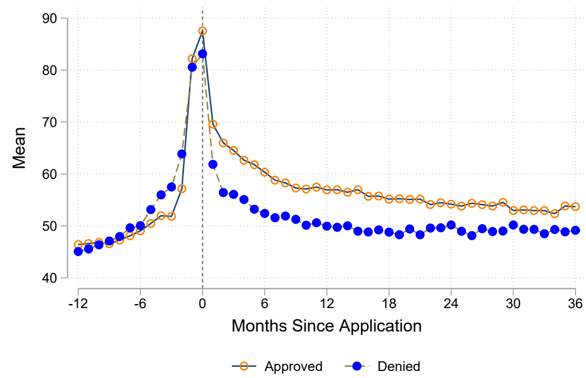
In panels (c)-(e), I plot the fraction of applicants who (i) visited a GP, (ii) received mental health treatment, and (iii) received treatment for a physical injury. All three exhibit a spike in the months before application, with elevated levels among approved applicants afterward. The spikes in mental health and physical injury represent potentially work-limiting health shocks, which also trigger a GP visit. On the contrary, there is no spike in treatment for respiratory illnesses such

Figure 2: **Universally-Insured Health Spending Around Time of Application**

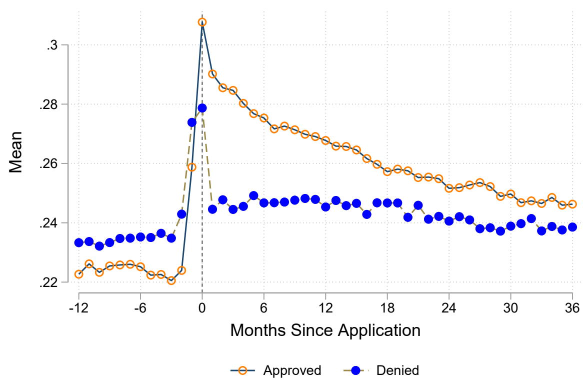
(a) **Probability of Receiving Medical Care**



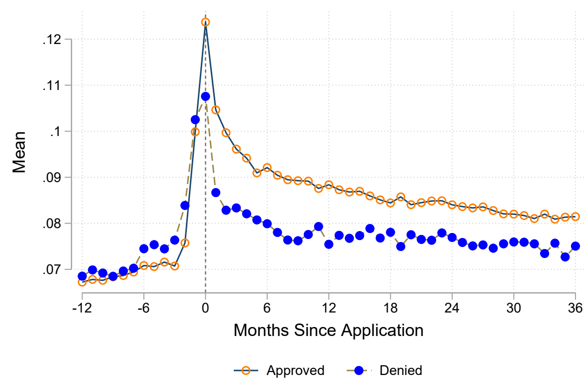
(b) **Hospital and Outpatient Spending**



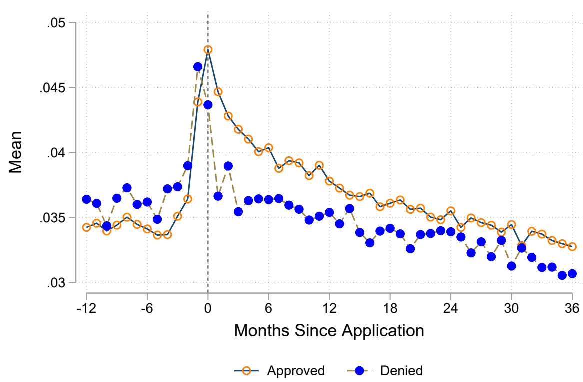
(c) **General Practitioner (GP) Visit**



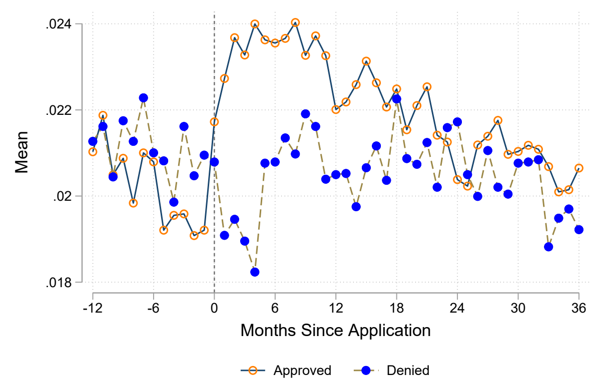
(d) **Mental Health Treatment**



(e) **Physical Injury**



(f) **Respiratory and Flu**

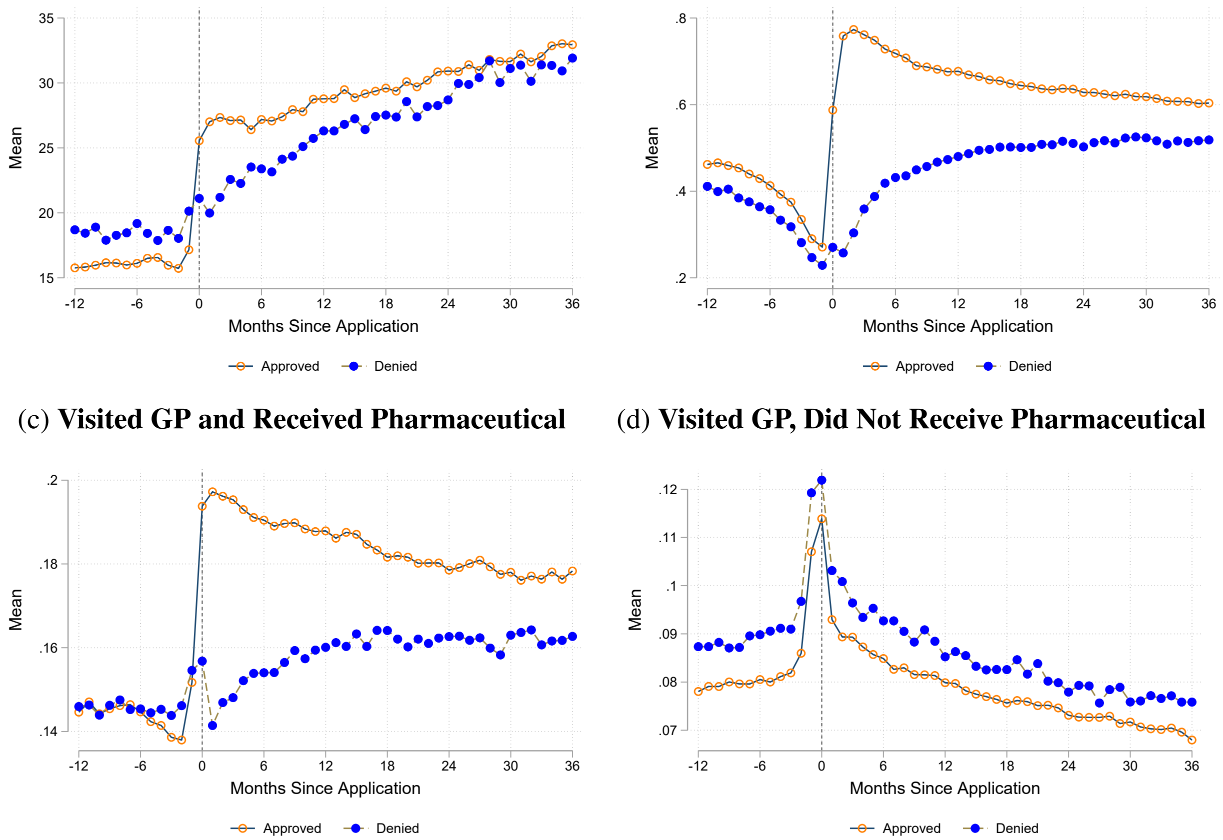


Note: Average outcomes in each month around the time of application are plotted for the set of EDP-reviewed applications, separately for approved and denied applicants. The outcomes are (a) an indicator for receiving any hospital or outpatient treatment, (b) hospital and outpatient spending, (c) an indicator for visiting a general practitioner; (d) an indicator for receiving mental health treatment; (e) an indicator for receiving treatment for physical injury; (f) an indicator for receiving treatment for respiratory illness.

as influenza (panel (f)), consistent with these being mostly minor health events that do not inhibit work. However, among approved applicants, treatment for respiratory illness increases by 25% after the application, which is consistent with IA recipients having more time available to seek health care (due to not working full-time).

Figure 3: **Pharmaceutical Spending Around Time of Application**

(a) **Drug Costs** (b) **Fraction of Drug Costs Paid by Government**



Note: This figure plots average outcomes around the time of application among the set of VO-reviewed applications, separately for those that were approved and those that were denied. The outcomes are (a) total pharmaceutical spending, (b) the fraction of drug costs paid by the government, (c) an indicator for visiting a GP in the same month that a pharmaceutical prescription was filled, and (d) an indicator for visiting a GP without a prescription filled in the month.

Pharmaceutical outcomes are shown in Figure 3. Drug spending does not spike before application, but increases sharply afterward among approved applicants, consistent with subsidy-induced spending: For approved applicants, the fraction of drug costs paid by the government increases from 23% in the month before to 78% in the month after (panel (b)).[25] The drug spending gap

[25] IA recipients receive a 100% subsidy for eligible drugs. The less-than-100% rate in Figure 3 comes from two

between approved and denied applicants decreases over time, mimicking the gap in government drug reimbursement in Figure 3 and the pattern of IA receipt in Figure 1. The elevated frequency of GP visits after the application among approved applicants is driven by patients that filled a prescription in the same month (panels (c) and (d) of Figure 3), suggesting that the drug subsidy also increases outpatient spending associated with writing prescriptions.

Extensions: Trends are very similar for the full sample of applicants, as opposed to only those reviewed by a VO (section B.5). Health spending does not spike among children that can be linked to adult applicants, but pharmaceutical consumption minorly increases among children of approved parents after the application, consistent with the subsidy (section B.6).

Interpretation: Do health shocks *cause* an application for welfare? Or, do people experience health-unrelated unemployment, which causes them to seek health care and simultaneously apply for welfare? The latter is possible if unemployment frees up time to seek health care. However, empirically, there is no pre-application increase in health care for children, which would plausibly be affected by parental time availability. Nor is there a pre-application increase in pharmaceutical spending or respiratory-related health care. These patterns are more consistent with the interpretation that health shocks are the proximate cause of applications for welfare.

Summary: These findings suggest that the cash welfare system insures health risk despite not being explicitly designed to do so. Furthermore, approved applicants have higher health spending long after the application. In the next section, I estimate whether these health spending differences are, at least partially, caused by being granted access to welfare itself.

4 Causal Effects of Application Approval

4.1 Potential Mechanisms

Precarity and Financial Distress: Welfare provides income support of last resort which may prevent people from entering more precarious circumstances.[26] By preventing precarity, and negative health events that follow from it, welfare may improve health and reduce health spending. Recent studies find very limited effects of income shocks on health and health care (*e.g.*, Cesarini et al.

sources: (1) someone that fills a prescription early in the month, then becomes an IA recipient later in the same month, would not have had coverage for that drug spending. (2) A small subset of IA recipients are in the category of "hardship assistance", which does not automatically imply drug coverage.

[26]This could mean avoiding eviction, avoiding an abusive spouse, avoiding illicit activities, and so forth.

(2016), Adda, Banks and von Gaudecker (2009)), but these income effects are measured for the broader population, rather than households in severe financial distress.

Time Use: If being approved for welfare reduces employment, it will also increase non-work time. If medical care increases with time availability, then gaining access to welfare may increase healthcare spending.

Promotion of Medical Care: Recipients get more generous pharmaceutical subsidies than non-recipients, which promotes medication use and visits to physicians that prescribe them. Case workers may also encourage recipients to seek medical care; they were trained to understand the health benefits available to IA recipients, both universally insured services and supplemental subsidies.[27]

Risky Behaviors and Idleness: Welfare may promote risky behaviors and disincentivize the pursuit of long-run employment growth, both of which could worsen health. The evidence on changes in risky behaviors is mixed: among mothers pushed off welfare due to reform in the US, Basu et al. (2016) find increased binge drinking, Kaestner and Tarlov (2006) find the opposite, and Corman et al. (2013) find reduced illicit drug use.[28][29]

4.2 Causal Setup

The goal is to estimate the effect of application approval in time t on outcomes in $t+h$. Denote application approval as $D_{i,t} = 1$, denial as $D_{i,t} = 0$, and outcomes as $Y_{i,t+h}$. The subscript h denotes the first, second, or third post-application year.[30] The outcome determination model is:

$$Y_{i,t+h} = \beta_{i,t+h} D_{i,t} + \alpha_{t,o} + \beta_Y Y_{i,t-1} + \eta_{i,t} \quad (1)$$

Where $\alpha_{t,o}$ represents office (o) by application year (t) fixed effects. I also control for individual i's pre-application outcome $Y_{i,t-1}$, which tends to improve the precision of the estimated effects.

[27]The IA manual states: "It is important for staff to be familiar with the rules of eligibility for health benefits and services for recipients of all other Income Support Programs. These program rules and relationships are an important component of on-the-job and residential core training of financial assistance workers [case workers]." (Ministry of Human Resources, 1997*b*)

[28]The mechanisms for changes in illicit drug use are unclear – it could be that mothers returning to work face drug tests which deter drug use. It could also be changes in income or time use.

[29]Dobkin and Puller (2007), Riddell and Riddell (2006), and Evans and Moore (2011) document adverse health events around the day that welfare checks are issued. However, this does not necessarily mean that welfare worsens health but rather that concentrated income bursts promote risky behaviors. Indeed, adverse health events follow more general income receipt, such as the payday of public bureaucrats (Andersson, Lundborg and Vikström, 2015).

[30]The first post-application year is months 1 to 12 following application in month 0. The second post-application year is months 13 to 24, and so on.

For individual i in application year t, the causal effect of being approved on outcomes in $t+h$ is $\beta_{i,t+h}$. The parameter of interest is some weighted average of treatment effects $\beta_{i,t+h}$. I identify this weighted average using the variation in adjudicators' propensity to recommend an application for approval ("leniency") as an instrument for $D_{i,t}$.

Random Assignment: This approach requires that the assignment of adjudicators is independent of potential outcomes. Since adjudicators are specific to field offices throughout the province, the composition of applications that each adjudicator receives varies with regional differences in the applicant pool. I condition on office fixed effects to account for these differences. Then the assumption is that, within an office, assignment is random. I go a step further by including office-by-year fixed effects to allow regional differences to change over time.

As discussed in Section 1, adjudicators were assigned applications on a first-come-first-serve basis within an office — whichever adjudicator had availability would receive the application for review. Adjudicators did not specialize in particular types of applicants. These institutional features imply that adjudicator assignment was likely random. To support this assumption, in section 4.3, adjudicator leniency is shown to be uncorrelated with a rich set of applicant characteristics.

Exclusion Restriction: Identification also requires that adjudicators affect post-application outcomes only through their effect on application approval ($D_{i,t}$). This is likely true. Adjudicators only evaluated applicants' eligibility for welfare — they did not determine eligibility for other supports such as subsidized housing. Adjudicators may not even interact with applicants unless an interview is conducted as part of the investigation process.

Estimation: The typical approach to using adjudicator leniency has been to estimate adjudicator fixed effects with the application decision as the outcome variable: $D_{i,t} = V_{j(i,t)} + \gamma_{t,o} + u_{i,t}$, where $V_{j(i,t)}$ are adjudicator fixed effects.[31] Then, their estimated counterparts $\hat{V}_{j(i,t)}$ are used as a just-identified continuous instrument for $D_{i,t}$ in equation (1). To avoid mechanically violating the independence assumption, $\hat{V}_{j(i,t)}$ are estimated on a leave-out-i basis. In my case, I leave out the entire family unit since families apply jointly.

This approach is equivalent to including adjudicator dummy variables directly as instruments for $D_{i,t}$ in the jacknife instrumental variable estimator (JIVE) proposed by Angrist, Imbens and

[31] Examples of this approach are Maestas, Mullen and Strand (2013) and Black et al. (2018). I follow Dobbie, Goldin and Yang (2018) in allowing adjudicator fixed effects to differ in each year. I show below substantial year-over-year persistence in each adjudicator's measured leniency.

Krueger (1999). However, the JIVE can be biased when there are many control variables (Kolesar, 2013) — in my case, the office-by-year fixed effects. Therefore, I employ the unbiased jacknife instrumental variable estimator (UJIVE) proposed by Kolesar (2013) and recently used by Norris, Pecenco and Weaver (2021), which performs well with many control variables. Just like the JIVE, the UJIVE can be implemented by estimating $\hat{V}_{j(i,t)}$, then using $\hat{V}_{j(i,t)}$ as a continuous instrument for $D_{i,t}$ in a two-stage least squares estimator of equation (1). See Appendix C for more details.

Recommendation versus Actual Approval: Rather than using application approval ($D_{i,t}$) to estimate adjudicators' leniency, I use their recommendation $R_{i,t}$. So, in the first step, adjudicator fixed effects are estimated by:

$$R_{i,t} = V_{j(i,t)} + \gamma_{t,o} + u_{i,t} \tag{2}$$

and estimated $\hat{V}_{j(i,t)}$ are used as instruments for $D_{i,t}$ in equation 1. As noted in Section 1, VOs only made recommendations. Intake Officers did not follow the recommendation in 30% of cases. Using $R_{i,t}$ rather than $D_{i,t}$ is justified by the concern that some applicants are better at influencing the Intake Officers' final decisions. For illustration, assume that all VOs are equally lenient and randomly assigned applications. By pure chance, some VOs will be assigned more applicants that are strong self-advocates. Even if the VO recommends rejection, strong self-advocates can persuade Intake Officers to disregard that recommendation. This makes some VOs seem more lenient when measured using approval. This issue disappears when the number of applications reviewed by each VO becomes large, but the number of applications per VO is quite finite.

Inference: Most, if not all, applications of jacknife estimators to "judge fixed effect" IV strategies use the 2SLS asymptotic distribution to calculate standard errors (e.g., Norris, Pecenco and Weaver (2021); Bhuller et al. (2020); Dobbie, Goldin and Yang (2018); Maestas, Mullen and Strand (2013)). I follow this convention. In doing so, I cluster standard errors at the adjudicator-year level, which is the effective level of random assignment.[32]

Monotonicity: To interpret the estimand as a weighted average of treatment effects among compliers, some form of monotonicity must hold. Strict (or pairwise) monotonicity assumes that if

[32] The 2SLS limiting distribution can differ from that of the jacknife estimator when the number of instruments grows with the sample size. Chao et al. (2012) derive the limiting distribution of the jacknife estimator under heteroskedasticity in this case, and Mikusheva and Sun (2021) develop inference that works under less restrictive conditions.

applicant i is more likely to be approved with adjudicator j than with adjudicator k, then the same must be true for *all applicants*. Strict monotonicity is a tall order, however. Frandsen, Lefgren and Leslie (2023) develop a test that jointly tests the exclusion restriction and strict monotonicity. Both Dobbie, Goldin and Yang (2018) and Norris, Pecenco and Weaver (2021) fail this test, as does my setup. Fortunately, a weaker form of monotonicity (*average monotonicity*) still allows the estimand to be interpreted as a weighted average of treatment effects among compliers (Frandsen, Lefgren and Leslie, 2023).[33] Average monotonicity requires only that for any applicant i, the covariance between their approval outcome ($D_{i,t}$) and adjudicators' leniency is positive. I adopt this assumption and, in the following section, show evidence that it holds.

Analysis Sample Restriction: I restrict the sample to adjudicator-year pairs in which the adjudicator reviewed at least 25 applications to remove imprecisely estimated leniency measures from the first stage. I restrict to office-year pairs in which there were at least two adjudicators, to ensure there is always a within-year-within-office comparison of adjudicators. Table B.1 shows that these restrictions reduce the sample from 156,819 to 98,953 applicants without changing their average characteristics. In this analysis sample, there are 350 adjudicators that were present in the data for 2 years on average. Each adjudicator reviewed an average of 148 applications per year.

I focus on adults aged 19 to 60 years. The sample of children linked to their parents' application is small. And among these children, there is no change in health around the time of application and no difference between those whose parents were approved versus denied (see Section B.6).

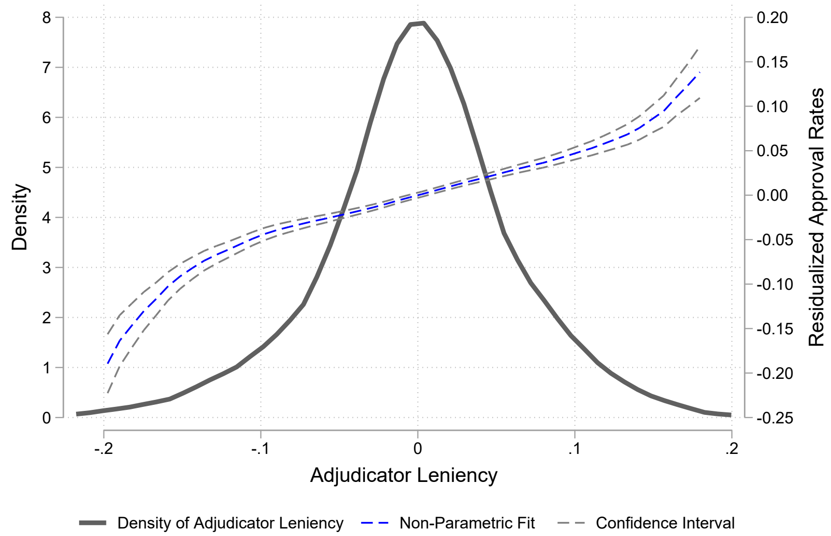
4.3 First Stage Tests

To assess the underlying variation in adjudicator leniency, in Figure 4, I plot the distribution of estimated leniency ($\hat{V}_{j(i,t)}$ estimated from equation (2)) and a local linear regression of application approval on $\hat{V}_{j(i,t)}$. The 1st and 99th percentiles of leniency are -0.197 and 0.179, respectively, and moving between these percentiles increases the approval probability by 32 percentage points.

In Table 2, I show the first stage coefficient from the regression $D_{i,t} = \pi \hat{V}_{j(i,t)} + e_{i,t}$ for the full sample, childless adults, and parents. In the absence of measurement error, π should be equal to 0.7, since the VOs' recommendations are followed in 70% of cases. The estimate of π is instead

[33] The weights are the covariance between the individual's adjudicator-specific treatment status and adjudicators' average treatment propensities across the full sample.

Figure 4: **Adjudicator Leniency and Approval Rates**



Note: The first series is the density of estimated adjudicator leniency (as described in the text). The second series is the kernel-weighted local linear regression (with a bandwidth of .02) between leniency and application approval, after controlling for office-by-year fixed effects. The 95% confidence intervals are also shown. Adjudicator leniency is residualized at the 1st and 99th percentiles for the purpose of graphing.

0.462, which is consistent with measurement error in $\hat{V}_{j(i,t)}$.[34] The F statistic for this first-stage relationship is 479 in the full sample, 337 among childless adults, and 220 among parents. By linearity of the first stage, the share of compliers in the sample is $\pi \times (V_{max} - V_{min})$. The estimate of this is 0.35, indicating that approximately one-third of the sample are compliers.

Table 2: **First Stage: Adjudicator Leniency on Application Approval Probability**

	(1) Full	(2) Childless	(3) Parent
Adjudicator Leniency	0.462 (0.0211)	0.483 (0.0263)	0.433 (0.0292)
Observations	98333	52051	46282
F-statistic	479.7	337.0	220.9
Year-over-Year Correlation in Adjudicators' Leniency	0.461		
Approximate Complier Share	0.354	0.360	0.332

Note: This table shows the estimated effect of leniency on application approval for the full sample, childless adults, and parents. Regressions control for office-year fixed effects and cluster standard errors at the adjudicator-year level. The Year-over-Year Correlation in Adjudicators' Leniency is $Cor(\hat{V}_{j,t}, \hat{V}_{j,t+1})$.

[34] Attenuation of the first stage coefficient appears common in many papers using idiosyncratic variation in "judges". For example, the first stage coefficient in Autor et al. (2019) is approximately 0.82, in French and Song (2014) roughly 0.7, and in Maestas, Mullen and Strand (2013) about 0.3.

Supporting Random Assignment: Under random assignment, $\hat{V}_{j(i,t)}$ should be orthogonal to applicant traits. To test this prediction, I regress $\hat{V}_{j(i,t)}$ on applicant traits observed in the 12 months before the application and office-by-year fixed effects. The results are shown in Table 3. Of the 14 included characteristics, only one is significant at the 5% level (spending on treatment for respiratory illness), while the full set is not jointly significant. However, these 14 characteristics strongly predict application approval.

Supporting Average Monotonicity: A testable implication of average (and strict) monotonicity is that $\hat{V}_{j(i,t)}$ constructed using the full sample should non-negatively correlate with application approval in all subsamples of the data (Frandsen, Lefgren and Leslie, 2023). Following this logic, I split the sample based on five characteristics: above vs. below median age, childless vs. parents, female vs. male, first-time vs. prior user, and above vs. below total medical spending. I then take all combinations of those two-way splits for 32 groups in total. For each, I estimate the first stage equation ($D_{i,t} = \pi \hat{V}_{j(i,t)} + \gamma_{t,o} + u_{i,t}$), and plot the estimates of π and the their T statistics in Figure 5. Every $\hat{\pi}$ is positive, and the majority are significant at the 5% level, implying that average monotonicity is a plausible assumption.

Characterizing Compliers: I follow the approach used by Norris, Pecenco and Weaver (2021) to estimate the average characteristics of compliers.[35] Table B.2 shows the average characteristics of the full sample and the compliers. Most notably, 64% of compliers are childless compared to 53% in the full sample, and as a result, more likely to be male. They are also more likely to have received welfare previously — only 16% are first-time users, compared to 23% in the full sample. Like the full sample, compliers experience a large increase in health spending before an application, and have similar average health spending over the 12 months preceding an application.

4.4 Causal Effects on Post-Application Outcomes

In Figures 6 and 7, treatment effects (from equation 1) are plotted for each post-application year and outcome. The estimated effects on the cumulative three-year outcomes are shown in Table 4.

Panel (a) of Figure 6 plots the effect on extensive margin IA use. In the first post-application year, approval causes a 68 p.p. increase in IA receipt. This is less than 100 p.p. because 32% of denied applicants reapply and receive IA. By the third post-application year, the effect of approval

[35] Specifically, with a second stage of $X_{i,t}D_{i,t} = \kappa D_{i,t} + \alpha_{t,o} + v_{i,t}$ and the first stage $D_{i,t} = \pi \hat{V}_{j(i,t)} + \gamma_{t,o} + \epsilon_{i,t}$, the 2SLS estimate of κ is the estimate of $E[X_{i,t} \mid \text{Complier}]$.

Table 3: **Correlation Between Adjudicator Leniency and Applicant Characteristics**

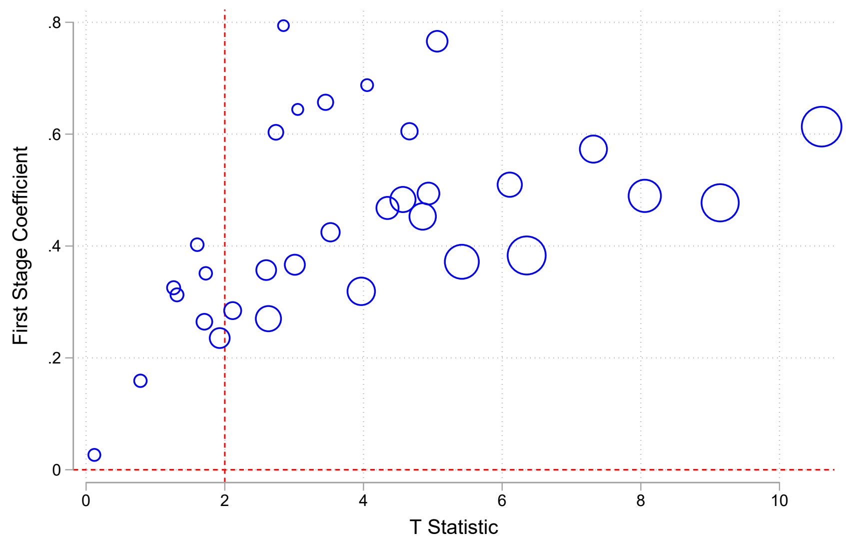
	Approved	Leniency
Age	0.00310	0.00200
	(0.00114)	(0.00240)
Age Squared	-0.0000498	-0.0000366
	(0.0000149)	(0.0000308)
Childless Man	-0.00813	0.0179
	(0.00407)	(0.0104)
Childless Woman	0.00731	0.00802
	(0.00477)	(0.00998)
Male Parent	-0.0197	-0.000775
	(0.00393)	(0.00766)
Employer Paid Premiums	-0.0250	-0.0166
	(0.00474)	(0.00976)
Resident Prior to Application	-0.0327	0.00157
	(0.00517)	(0.0141)
No IA History	-0.0981	-0.0131
	(0.00437)	(0.00764)
Total Hospital and Outpatient Spending	-0.00686	0.0106
	(0.00468)	(0.0132)
Mental Health Spending	0.00464	0.00702
	(0.00284)	(0.00604)
Respiratory Illness Spending	-0.00347	-0.0149
	(0.00320)	(0.00736)
Injury Spending	-0.00250	-0.00164
	(0.00309)	(0.00717)
GP Visit Spending	-0.00752	0.000509
	(0.00215)	(0.00435)
Drug Spending on Mental Health	-0.00653	-0.0102
	(0.00376)	(0.00754)
Drug Spending	-0.0000127	-0.000647
	(0.00335)	(0.00604)
Observations	98942	98322
F statistic for joint significance	47.24	1.661

Note: Application approval and adjudicator leniency are regressed on pre-application applicant characteristics and office-by-year fixed effects. Leniency and the spending variables are normalized to standard deviation 1. Spending is cumulative over the 12 months before application and winsorized at the 99th percentile. *Resident Prior to Application* indicates whether the person was in the data before application. Standard errors are clustered at the adjudicator-year.

is less than 5 p.p..[36] Green and Warburton (2004) found the same result, and demonstrated that the zero long-term treatment effect is driven foremost by approved applicants exiting welfare, and

[36]Of that 5 p.p., 2 p.p. is attributable to persons that transitioned to disability insurance (see Figure B.10).

Figure 5: **Average Monotonicity**



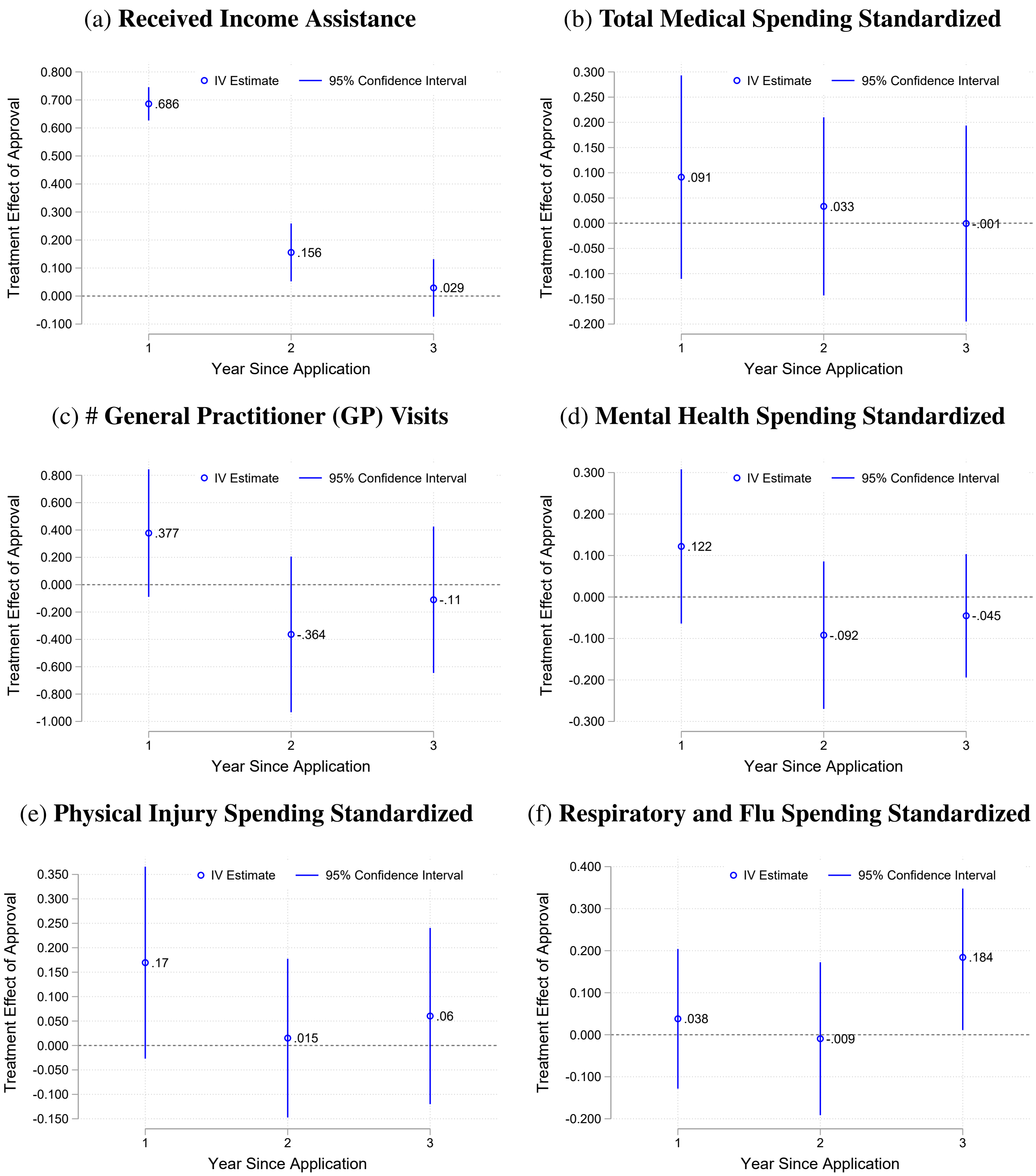
Note: I split the sample based on five characteristics: above vs. below median age, childless vs. parents, female vs. male, first-time vs. prior user, and above vs. below total medical spending. I then take all combinations of those two-way splits, for 32 groups in total. For each, I estimate the first stage equation ($D_{i,t} = \pi \hat{V}_{j(i,t)} + \gamma_{t,o} + \epsilon_{i,t}$), and plot the estimates of π and their T-statistics. The circle size is proportionate to the # of observations in the group.

secondarily by a small sub-group of denied applicants eventually gaining access. The implication is that for most applicants, being granted welfare is not a permanent change in transfers but rather medium-term support in the face of health and employment shocks.

Table 4 shows that, over three years after application, the causal effect of approval is approximately 6 months of benefits, corresponding to \$4000 (2002 CAD) in total, or \$705 per month. As a reference point, \$705 is equivalent to 88 hours of work at the minimum wage in 2002. These causal effects are not the average amount that an approved applicant receives but rather the difference between what approved and denied applicants receive.

Turning to health spending, benefit approval causes hospital and outpatient spending to increase by a statistically insignificant \$296, or 0.06 standard deviations. Or, put differently, every dollar issued in IA benefits is associated with 7.5 cents ($\frac{296.80}{3958.15}$) in universally-insured medical spending. Most of this effect derives from the first year after application, as shown in Figure 6. There are similar effects (in terms of standard deviations) on injury and mental health spending. Spending in both of these categories spiked before application, so the minor positive effects on post-application spending could mean that gaining access to welfare grants individuals the time to seek treatment (due to not working) for the health shocks that led them to apply for welfare and/or the encour-

Figure 6: **Dynamic Treatment Effects on IA Receipt and Health Spending**



Note: IV effects of application approval on outcomes in each year following application are shown, along with 95% confidence intervals. The outcomes, in order, are: (a) whether the applicant received IA in the year, (b) total non-pharmaceutical medical spending, (c) the number of visits to a general practitioner, (d) spending on mental health treatment, (e) spending on physical injury, and (f) spending on respiratory illness. Spending variables are winsorized at the 99th percentile in each year and are standardized to have a standard deviation equal to one in each year. Standard errors are clustered at the adjudicator-year level.

agement by case workers to do so. Consistent with this interpretation, there is no causal effect on treatment for respiratory illnesses (panel (f)) which did not exhibit pre-application spikes.

Table 4: **Effects on Cumulative Three Year Outcomes**

	β	SE
IA Receipt		
Dollar Amount of IA	3958.15	1144.59
Months of IA	5.67	1.45
Health Spending in Dollars (2002 CAD)		
Hospital and Outpatient Spending	296.80	482.98
Total Pharmaceutical Spending	408.35	164.57
Injury Spending	34.61	19.25
Mental Health Spending	-6.35	58.89
Cold and Flu Spending	6.71	4.28
Mental Health Pharmaceutical Spending	158.17	72.52
Health Spending in Standard Deviations		
Hospital and Outpatient Spending	0.06	0.09
Total Pharmaceutical Spending	0.20	0.08
Injury Spending	0.18	0.10
Mental Health Spending	-0.01	0.09
Cold and Flu Spending	0.14	0.09
Mental Health Pharmaceutical Spending	0.18	0.08

Note: This table shows the estimated effect of application approval on cumulative outcomes over the subsequent three years. That is, the outcome is $Y_{i,t+1} + Y_{i,t+2} + Y_{i,t+3}$. Spending variables are winsorized at the 99th percentile. Standard errors are clustered at the adjudicator-year.

Unlike hospital and outpatient care, there are large increases in pharmaceutical spending: \$408 or 0.2 standard deviations over three years. About 40% of this increase ($\frac{158.17}{408.35}$) comes from drugs that are associated with mental health treatment. The effects are clearest in the first post-application year, where the treatment effect on total spending is \$172 (panel (a) of Figure 7).

These effects are likely subsidy-driven. In the first year, the subsidy granted to IA recipients decreases the percent of drug costs paid by the individual by 35.4 p.p.. Based on this, I calculate a price elasticity assuming that drug spending effects are driven solely by the subsidy. Using the average drug spending and fraction paid out-of-pocket in the year before application as the base (\$200 and 66%, respectively, as shown in Table 1), the price elasticity is -1.6 ($\frac{172/200}{-35.4/66}$). This elasticity captures both extensive and intensive margin spending changes. Elasticity estimates from other contexts are notably lower: Goldman, Joyce and Zheng (2007)'s meta-review finds elasticities from -0.2 to -0.6. The complier group in my study, however, is quite different than most studies — young and very low-income households as opposed to seniors.[37] The large elasticity is consistent with two complementary mechanisms: First, the complier group may be very price responsive due to their experiencing both severe financial constraints and poor health. Second, access to the welfare system may promote medication treatment for non-price reasons, such as interactions with case workers. Finally, the treatment effect on drug spending is more persistent than the effect on the drug subsidy — by the third post-application year, the effect on drug spending is still positive (albeit statistically insignificant) despite the effect on the subsidy converging to zero. This may indicate behavioral persistence in pharmaceutical reliance.

The increase in drug spending also increases GP visits (panel (c) of Figure 7). The number of GP visits that occurred in the same month that the patient fills a prescription increases by 0.299 annually due to application approval. This is 80% ($\frac{0.299}{0.377}$) of the total increase in GP visits.

Robustness and Extensions: In Figure B.11, the effects of application approval on mortality and fertility (among women) are plotted. Neither is statistically significant, but both outcomes are very rare, which lowers statistical power. In Appendix B.4, I show that benefit approval has no detectable long-term effect on the likelihood of remaining in the province. This means that the estimated effects of benefit approval on health are not attenuated by selective out-migration.

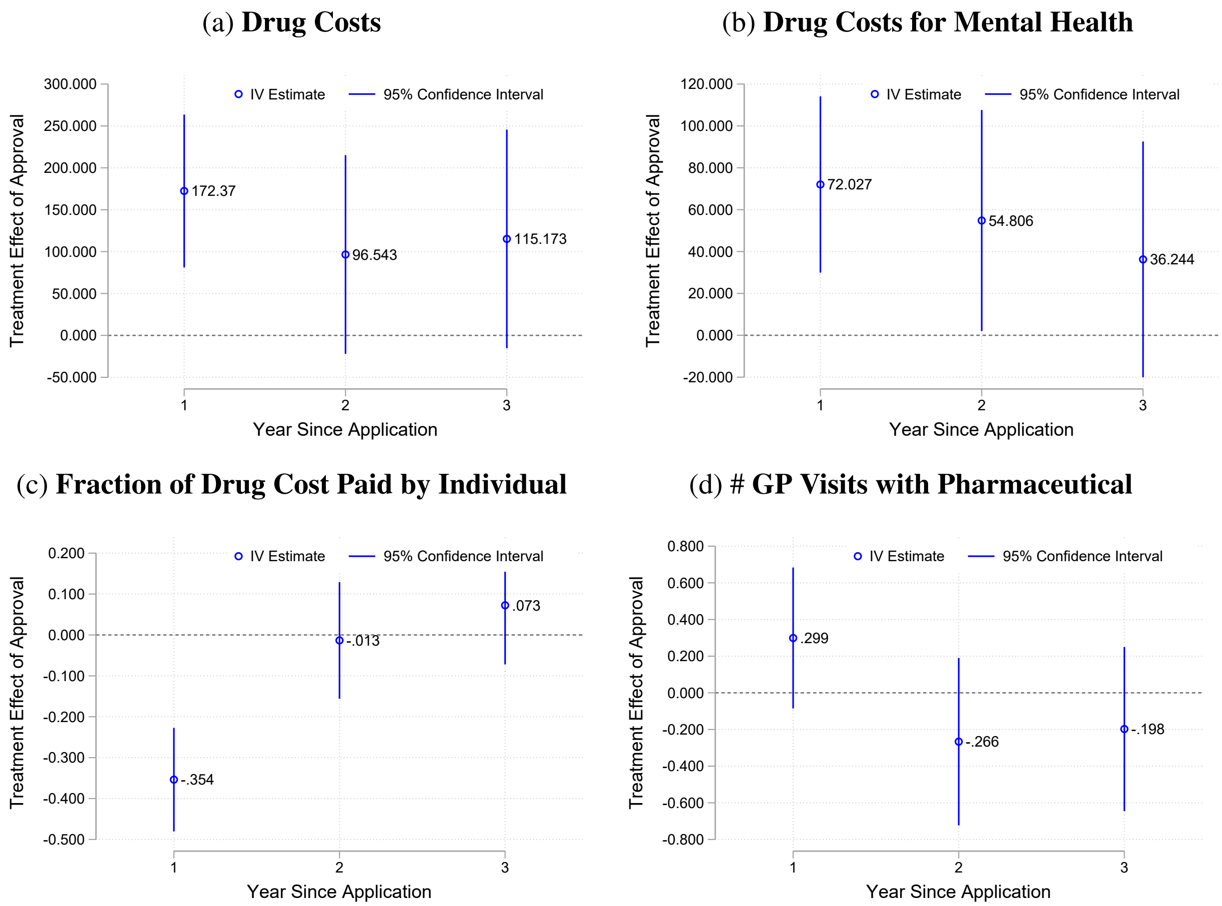
Summary: The almost-significant small positive effects in the first post-application year are consistent with (a) recipients having more time to access health care, (b) case workers encouraging recipients to seek treatment, and (c) the drug subsidy inducing physician visits for prescription writing. The large effect on pharmaceutical spending suggests that a lack of drug insurance among non-IA recipients strongly limits medication access among low-income households.

Comparison to Literature: These results are broadly consistent with Hicks et al. (2022) wherein we find mostly small effects on mother and child health spending from a Canadian welfare reform. My paper differs in that the majority of compliers are childless adults, as opposed to mothers with young children. Hicks et al. (2022) also use a different empirical strategy: the imposition of work search requirements. This distinction matters because the compliers generated from work search requirements were very employable, whereas the compliers in my paper may not be.[38]

[37]Prominent studies focus on Medicare Part D in the US (Yin et al., 2008; Einav, Finkelstein and Polyakova, 2018) which is a subsidy for seniors. Studies using the RAND Health Insurance experiments to estimate price elasticities struggle with the fact that the experiment changed health care prices beyond drugs, causing cross-price effects (Yeung et al., 2018). The same challenge faces studies of Medicaid expansion (e.g., Ghosh, Simon and Sommers (2019)).

[38]In Hicks et al. (2022), we linked income tax records to welfare *caseloads* to measure employment effects. In

Figure 7: **Dynamic Treatment Effects on Pharmaceutical Outcomes**



Note: This figure plots estimated effects of application approval on outcomes in each of the three years following application, and 95% confidence intervals. The outcomes are (a) total drug spending, (b) the fraction of drug costs paid by the individual among persons filling prescriptions, (c) the number of GP visits wherein a pharmaceutical prescription was filled in the same month, and (d) the number of GP visits without a prescription filled in the month.

Evidence from US welfare reforms similarly finds either no effect (Kaestner and Tarlov, 2006) or small positive effects (Basu et al., 2016; Narain et al., 2017) of welfare access on self-reported health among mothers.[39][40] Importantly, studies of US reform are confounded by changes in health insurance (Kaestner and Kaushal, 2003; Bitler, Gelbach and Hoynes, 2005; Cawley, Schroeder and Simon, 2006), since some former welfare recipients lost Medicaid coverage, which makes

the present paper, I was unable to link welfare *applications* to tax returns. And as discussed above, my proxy for employment very substantially undercounts employment, making it a weak basis for estimating employment effects.

[39]For instance, Basu et al. (2016) find that US welfare reform had small negative effects on self-reported “days of good mental health". In related work, Wickham et al. (2020) study the UK’s 2012 welfare reform that imposed additional conditionality, a longer waiting period for new applicants, and less frequent payments. They find suggestive evidence that these changes worsened self-reported mental health among unemployed individuals.

[40]This lack of contemporary effect may mask long-term health consequences driven by changes in unhealthy behaviors, such as drinking and smoking. Evidence on these outcomes is mixed, as described above.

it difficult to distinguish the effects of losing health insurance from the effects of losing welfare benefits. Indeed, Finkelstein et al. (2012) find that Medicaid insurance coverage strongly affects self-reports of healthiness and well-being, which fits with minor negative health effects of US welfare reform. It also fits with the findings of this paper: The most detectable causal effects are among pharmaceuticals, the one domain in which welfare access alters health insurance coverage.

4.5 Heterogeneity by Family Type

Unlike TANF in the US, Canadian IA programs provide welfare to both parents and childless adults. Childless adults may be affected quite differently by welfare access relative to parents. To assess this possibility, I estimate effects separately for each group.

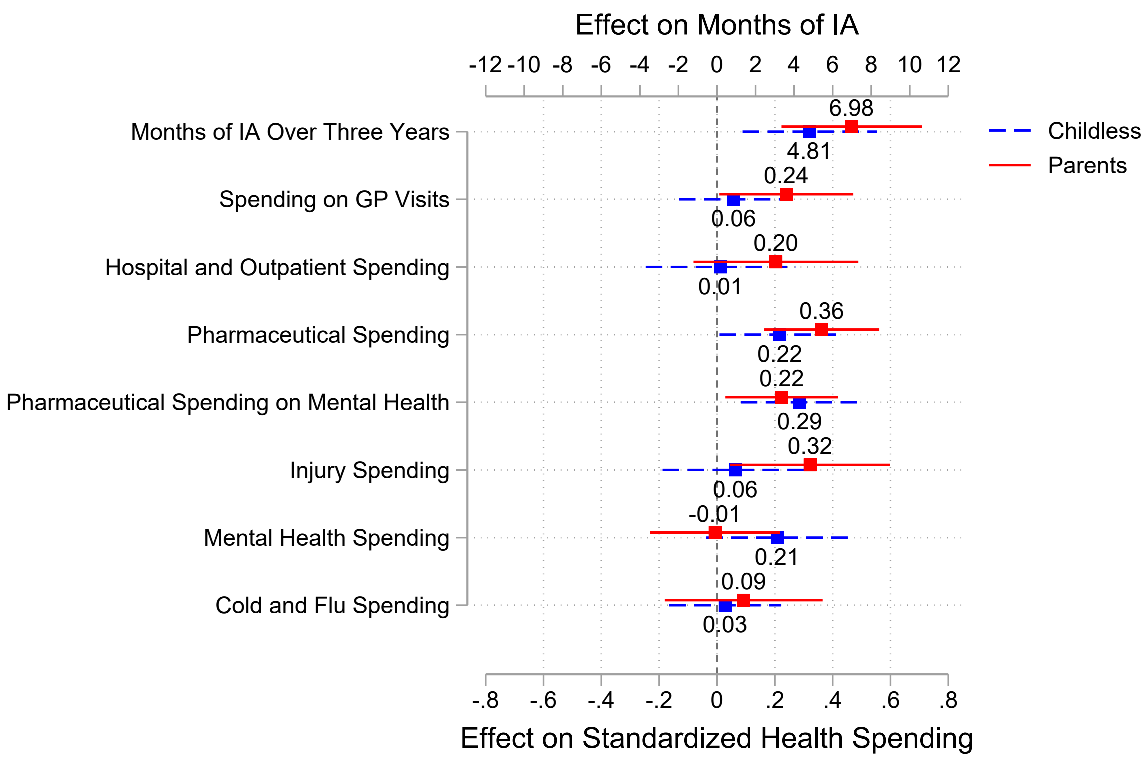
I estimate equation (1) separately for each group while instrumenting for application approval with leniency estimated from equation (2) using the full sample. Using $\hat{V}_{j(i,t)}$ from the full sample is permissible under the assumption of average monotonicity and improves precision by more precisely estimating adjudicator leniency. The first-stage coefficients for each group are shown in Table 2. I focus on health spending in the first post-application year, as this is where the almost-significant effects appeared in the full sample.

Estimates are shown in Figure 8. Point estimates are expressed in terms of *full sample* standard deviations, such that effect sizes are directly comparable across subsamples. Both parents and childless adults see increases in pharmaceutical spending, although more substantially among parents (0.36 versus 0.22 standard deviations). Childless adults are more likely to be treated for mental health in a hospital or outpatient setting and more likely to receive drugs for mental health treatment. In fact, mental health-related drugs make up 67.2% of the total effect on drug spending for childless adults but only 12% for parents.[41] Parents are more likely to see increases in GP visit spending, treatment for physical injuries, and pharmaceuticals unrelated to mental well-being.

The greater increase in GP visits among parents coincides with the greater increase in pharmaceutical spending. It is also consistent with Hicks et al. (2022) who find that a welfare reform reduced the frequency of GP visits for mothers and their children, which they partially attribute to

[41] Riddell (2020) analyzes the Canadian self-sufficiency project's (SSP) effects on self-reported mental well-being. The SSP provided a strong financial incentive to single mothers to transition from long-term welfare use to full-time employment. He finds that this program reduced feelings of depression 4-5 years after the initial experiment, at least in part due to elevated employment. Relatedly, Milligan and Stabile (2011) find that child tax benefits in Canada improve maternal self-reported mental health.

Figure 8: **Effects on Childless Adults and on Parents**



Note: This figure plots estimated effects of application approval on outcomes in the first post-application year and 95% confidence intervals, for childless adults and parents (as defined at the time of application). The point estimates are listed beside the markers. Treatment effects on the health spending variables are in standard deviation units. Spending variables are winsorized at the 99th percentile. Standard errors are clustered at the adjudicator-year level.

time constraints on single mothers who work full time. What about the increase in mental health treatment among childless adults (mainly men)? Men are ubiquitously less likely to seek treatment for mental health illness, relative to women, of their own accord (Galdas, Cheater and Marshall, 2005). In this context, gaining access to welfare and interaction with case workers may be the shove that men require to seek treatment for mental health issues. This interpretation, is, of course, speculative and should be considered a way marker for future research.

5 Generalizability and Discussion

On the one hand, I find that hospital and outpatient spending doubles before application, consistent with health degrading sharply before a welfare application. The spending spikes mostly dissipate over time, consistent with the health shocks being relatively short-term. The implication is that traditional cash welfare insures against short-term health shocks that are uninsured through other means. Stepner (2019) makes a related point for the Canadian tax and transfer system in general. He finds that 75% of income replacement after a hospitalization event comes from progressive taxes and transfers, as opposed to unemployment insurance and disability insurance.[42][43] His results, however, do not focus on whether welfare specifically is insuring health risk, and his focus on hospitalization represents the rarest and most acute of all health shocks. On the other hand, I show that approval for welfare has, at most, small positive effects on universally-insured health spending. From the government's perspective, each dollar spent on welfare generates 7.5 cents (statistically insignificant) of additional health expenditure.

Canada's cash welfare system resembles similar programs from other developed countries in fundamental ways: it provides cash to very low-income households, irrespective of health status, often conditional on searching for work, with compliance overseen by case workers. Canada's healthcare system also resembles most other developed countries — it provides universal insurance for medically necessary care. So the empirical results I document, and the mechanisms underlying them, are unlikely to be a uniquely Canadian phenomenon.

The one way in which Canada deviates is that it does not provide universal drug coverage, whereas most non-US developed countries do. The large effect on pharmaceutical spending, which is not universally insured but for which welfare recipients are subsidized, implies that a lack of insurance coverage substantially inhibits medication access among low-income households that cannot access welfare. My results, therefore, also inform recent policy developments and debates on expanding government-provided insurance coverage to pharmaceuticals (Health Canada, 2019) and other uninsured categories such as dental care (Robson, Schirle and Lindsay, 2022; Green, Rhys and Tedds, 2021) to low-income households.

[42]When measuring disability insurance, Stepner (2019) only counts federal disability benefits through the Canada Pension Plan. Disability insurance offered through the provinces he includes as a transfer in the broader tax system (part of the 75%) because provincial DI is lumped together with provincial "welfare" on tax slips.

[43]A related example is found in Arteaga and Barone (2022) who show that the Opioid crisis increased Supplemental Nutrition Assistance Program use.

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Appendix for Online Publication Only

Jeffrey Hicks

A Data Details

A.1 Building the Applications Dataset

To build a data set of applications, I use two administrative data sets. The first is the “pre-application" file. Persons who entered a field office seeking information about applying would be met by a front-line worker who would offer a preliminary assessment of whether the person may be eligible. Starting an application at this stage appears in the “pre-application" records. I consider the individual to be an applicant if they make it to this stage, regardless of whether they finish the application, and indeed many do not. They may find the hassle costs of gathering documentation too high. They may find work while they are proceeding with the application. They may realize that they are ineligible. If the person completes the application, it becomes eligible for review by a VO. Because families apply jointly for IA, I consider all adults listed on the application as applicants.

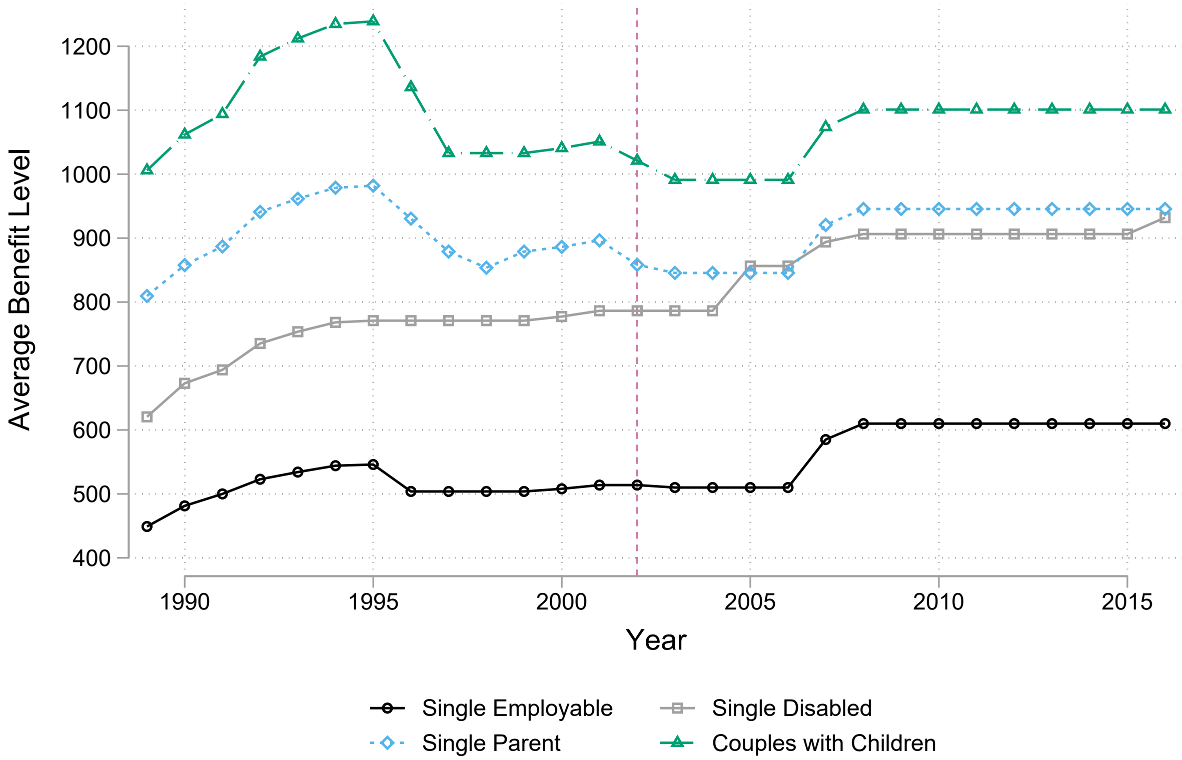
A.2 Costing of Hospital-Based Services

Each hospital visit is assigned a Resource Intensity Weight (RIW) based on the patient’s case mix. The RIW is then multiplied by a “Cost per Weighted Case", or CPWC, to derive that visit’s dollar value cost. The sum of RIW×CPWC within the provinces equates exactly to total hospital expenditure in the province, although for any given visit, RIW×CPWC may over- or under-estimate the true cost.

B Supplemental Results

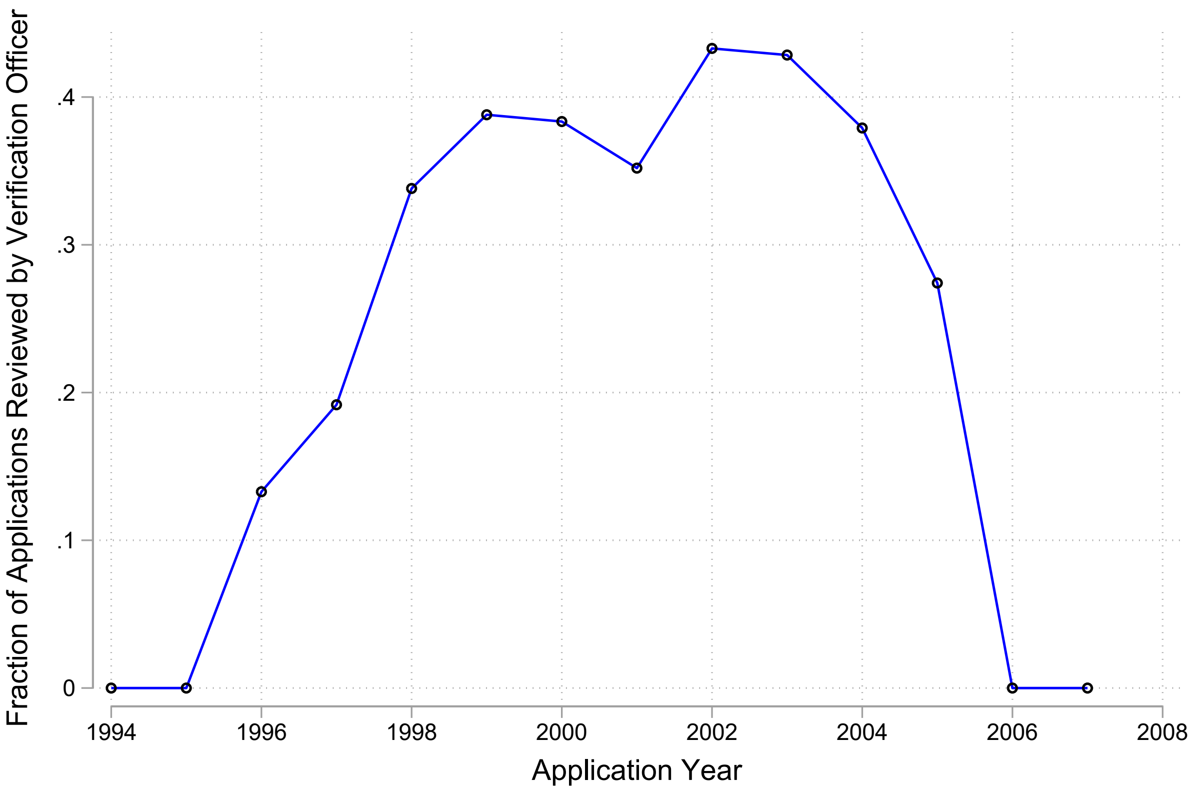
B.1 Institutional Trends

Figure B.1: **Average Monthly Benefit Rates**



Note: This figure plots average benefit level amounts for different recipient groups: single employable adults; single adults with a disability designation; lone parents with one child, age 2; and couples with two children, ages 10 and 15. Source: National Council of Welfare (various years) and Caledon Institute (various years).

Figure B.2: **Fraction of Applications Reviewed Under the Early Detection Program**



Note: This figure plots the fraction of applications that were reviewed by a Verification Officer (adjudicators) under the Early Detection Program (EDP) starting in 1996.

B.2 Descriptive Statistics

Table B.1: **Descriptive Statistics: All Reviewed Applications and Subset in the Analysis Sample**

	All Reviewed Applications				Analysis Sample of Reviewed Applications			
	All	$D = 1$	$D = 0$	ρ	All	$D = 1$	$D = 0$	ρ
Approved	0.76	1	0		0.76	1	0	
Parent	0.48	0.49	0.48	0.08	0.47	0.47	0.47	0.19
Female	0.44	0.44	0.43	0	0.43	0.43	0.43	0.11
Age	34.96	34.91	35.12	0	34.69	34.57	35.07	0
No IA History	0.23	0.2	0.31	0	0.24	0.21	0.31	0
Employer Paid	0.12	0.11	0.14	0	0.12	0.12	0.14	0
Any MSP or Hospital Treatment	0.72	0.71	0.74	0	0.72	0.71	0.74	0
Treated in Hospital	0.12	0.12	0.12	0.02	0.11	0.11	0.12	0.03
Outpatient (MSP) Spending	469.34	459.36	501	0	466.02	452.93	506.66	0
Hospital and Outpatient Spending	1048.3	992.6	1224.94	0	1046.1	982.62	1243.21	0
Visited GP	0.66	0.66	0.69	0	0.66	0.65	0.69	0
GP Visits Expenditure	124.98	123.86	128.52	0	122.54	120.4	129.18	0
Treated for Injury	0.26	0.26	0.27	0	0.26	0.25	0.27	0
Injury Expenditure	34.91	34.3	36.84	0.02	34.57	33.92	36.6	0.05
Treated for Colds	0.18	0.17	0.18	0	0.18	0.17	0.18	0
Colds Expenditure	9.15	9	9.64	0.07	8.94	8.73	9.57	0.07
Treated for Mental Health (MH)	0.3	0.3	0.3	0.19	0.3	0.3	0.3	0.14
MH Expenditure	86.64	83.35	97.09	0	87.12	83.31	98.93	0
Received Pharmaceuticals	0.63	0.63	0.63	0.01	0.62	0.62	0.63	0
Pharmaceutical Expenditure	200.87	193.94	222.84	0	193.57	184.32	222.3	0
Share Drug Cost Uninsured	0.66	0.65	0.71	0	0.67	0.66	0.72	0
Day Supplied	166.12	163.51	174.41	0	158.69	155.06	169.97	0
Received MH Pharmaceuticals	0.25	0.25	0.24	0	0.24	0.24	0.24	0.15
MH Pharma Expenditure	66.92	65.12	72.62	0	63.82	60.87	72.96	0
4-Year Mortality Rate	0.03	0.03	0.03	0.55	0.03	0.03	0.03	0.94
N adult applicants	118476	96102	32922	1	79878	63788	21593	1
N	156819	119224	37595	1	98953	74849	24104	1
N adjudicators	919	884	709	1	350	350	349	1
N adjudicator years	1885	1826	0.	1	666	666	665	1

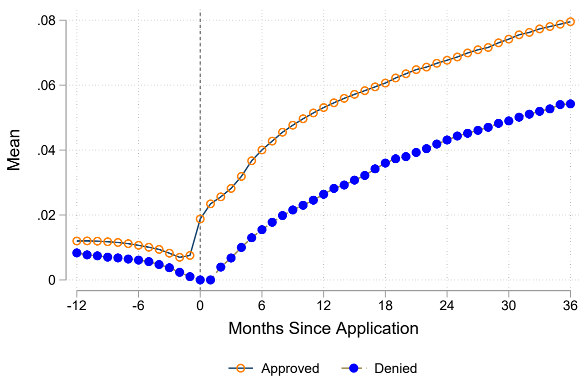
Note: This table shows average characteristics for the full set of applications reviewed under the EDP and the subset that are used in the analysis throughout the paper. $D = 1$ and $D = 0$ denote approved and denied applicants, respectively, while "All" denotes both combined. ρ is the p-value testing the difference in means between approved and denied applicants. Applicant demographic characteristics are observed as of the application. Health outcomes are measured over the 12 months prior to application.

B.3 Disability Insurance and Excused from Work Search on Medical Grounds

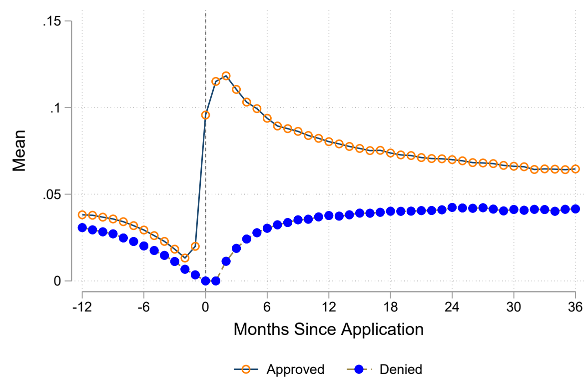
Some applicants for Income Assistance eventually transition onto full disability insurance. Panel (a) of Figure B.3 shows that, in my sample, less than 6% of applicants transition to DI within 1 year of the original application, and less than 8% within 3 years. Others start in, or transition to, categories of Income Assistance in which they are excused from searching for work; the most common reason being the presence of young children, but also due to "persistent barriers" or medical reasons. In panel (b), I plot the fraction of applicants excused from searching for work for any of these reasons.

Figure B.3: **Disability Insurance and Excused from Work Benefits**

(a) **Disability Insurance Receipt**



(b) **Income Assistance Receipt, Excused from Work Search**



Note: This figure plots average outcomes around the time of application among the set of VO-reviewed applications, separately for those that were approved and those that were denied. The outcome in panel (a) is an indicator for receipt of disability insurance. The outcome in panel (b) is whether the person received non-disability insurance income assistance, but in which they were exempt from searching for work.

B.4 Adjusting for Residence

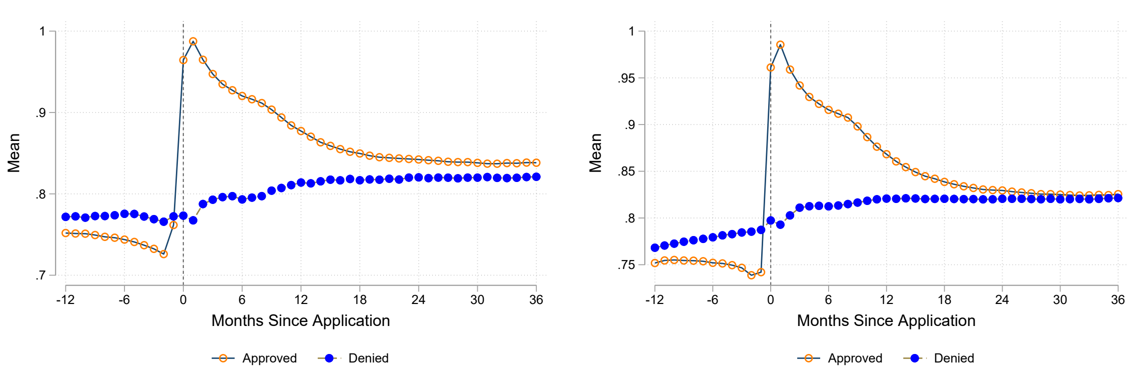
I do not observe an official indicator of residence in the province. I can, however, indirectly infer whether an individual is residing in the province as whether they appear in any of the administrative data sets that I access. The Medical Services Plan (MSP) registry is the most useful of these. All residents of the province are required by law to register for MSP and pay premiums. With full compliance, the MSP registry would therefore contain all residents in the province. The problem is that not all residents comply and pay, especially demographics on the margin of IA receipt. Additionally, IA recipients receive their MSP premiums paid for them by the IA ministry, implying that all IA recipients will appear in the registry. These two facts mean that low-income non-IA recipients will appear to have lower resident rates than IA recipients, even if true resident rates are equivalent.

I combine these records with health care treatment records to generate an indicator for whether an applicant was observed in *any* of the data sets in a given month, my best proxy of residence. In Figure B.4, I plot the fraction of applicants observed as residents. At its lowest point, the residency rate is 75%. Unsurprisingly, the residency rate among approved applicants spikes after benefit approval, since approved applicants are recorded in IA records. As a result, the pattern of residency among approved and denied applicants strongly mimics the pattern of IA receipt in panel (a) of Figure 1, indicating that inferred residency patterns are driven by the appearance in the IA data.

Figure B.5 shows the treatment effects of benefit approval on the proxy for residency, in each of the three years following application. There is a significant positive effect on inferred residency, consistent with approved applicants appearing as “residents" due to appearing in IA records. By year 2, the estimated treatment effect is approximately -2 percentage points and statistically insignificant. This suggests that benefit approval has no, or very limited, effects on the probability of remaining in the province, and thus the treatment effects estimates of approval on health outcomes are unlikely to be attenuated by selective out-migration.

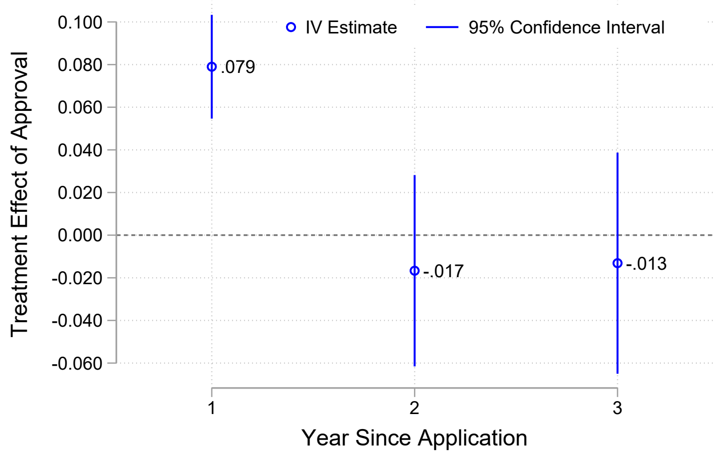
Figure B.4: **Residence Around Time of Application**

(a) **Full Application Data Set** (b) **Reviewed Applications**



Note: This figure plots the fraction of the sample that appear in any of the data sets, and thus inferred to be residing in the province, around the time of application. Panel (a) shows the full sample of applicants, panel (b) shows the sample of applicants that were reviewed by a Verification Officer.

Figure B.5: **Treatment Effects on Indicator for Being in Administrative Data (Residence)**

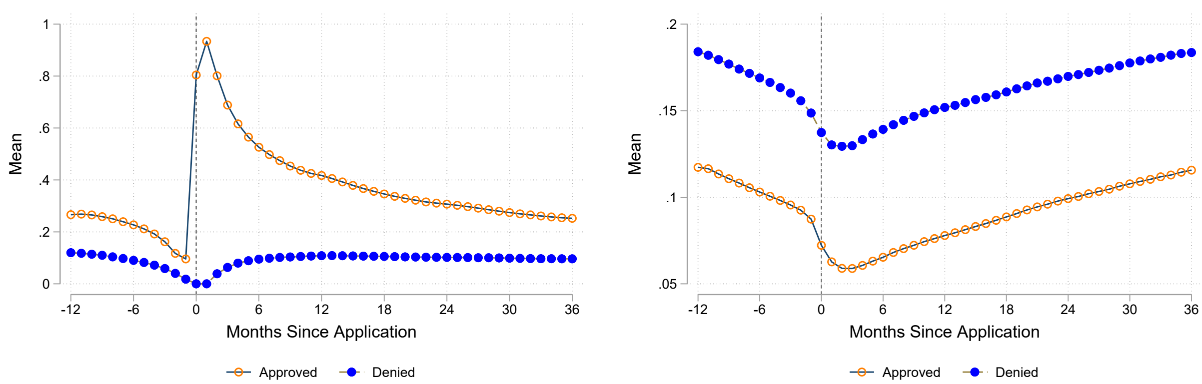


Note: This figure plots treatment effects of benefit approval on an indicator for whether the applicant appears in any of the administrative files, which serves as a proxy for residence. The estimators are described in section 4. 95% confidence intervals are shown. Standard errors are clustered as the adjudicator-year level.

B.5 Trends for All Applications Rather than VO-Reviewed Applications

Figure B.6: **Income Assistance and Employment Around Application for IA, Full Sample**

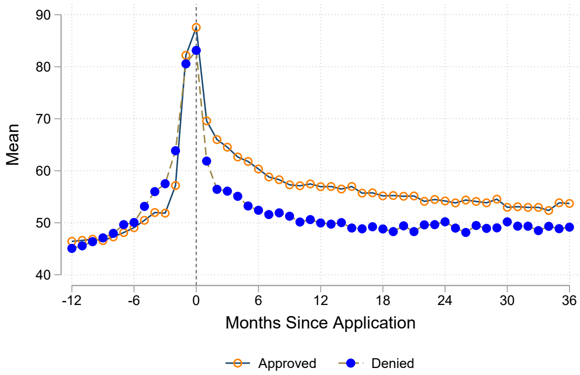
(a) **IA Use** (b) **Employer Paid Premiums**



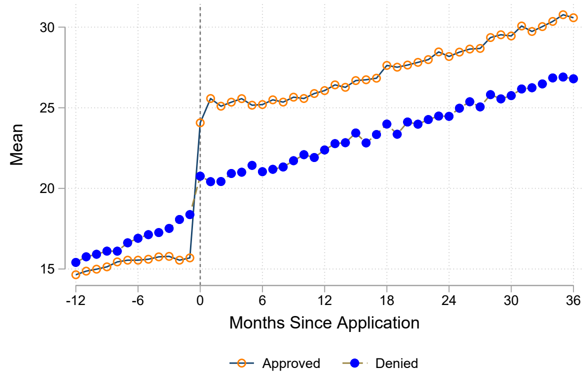
Note: This figure plots average outcomes around the time of application ($t = 0$) among the full set of applications, as opposed to only the EDP-reviewed applications used in the main text, separately for applicants that were approved and those that were denied. The outcome in panel (a) is welfare receipt. The outcome in panel (b) is whether the person had their health insurance premiums paid by an employer.

Figure B.7: **Health Outcomes Around Time of Application, Full Sample**

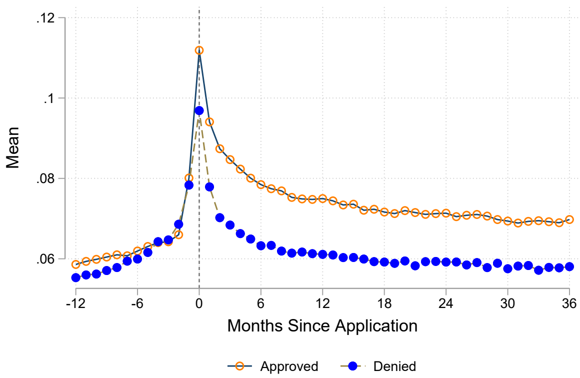
(a) **Hospital and Outpatient Spending**



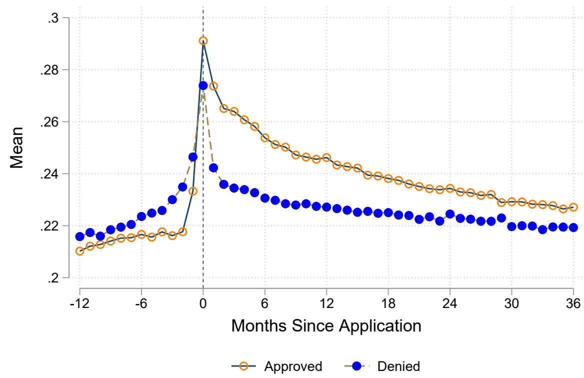
(b) **Drug Costs**



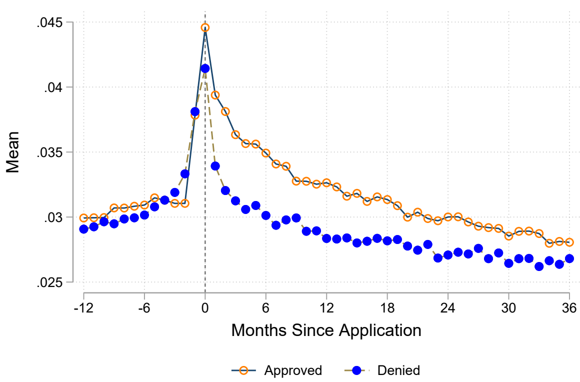
(c) **Mental Health Treatment**



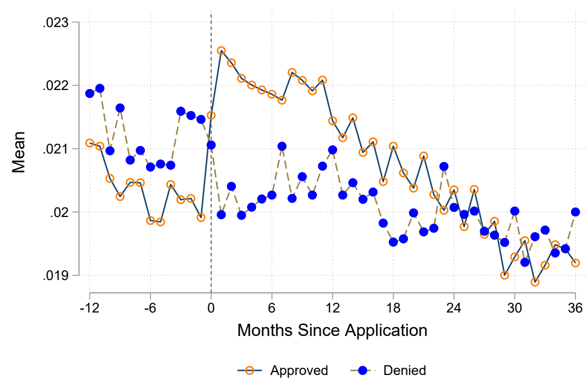
(d) **General Practitioner Visit**



(e) **Physical Injury**



(f) **Respiratory and Flu**



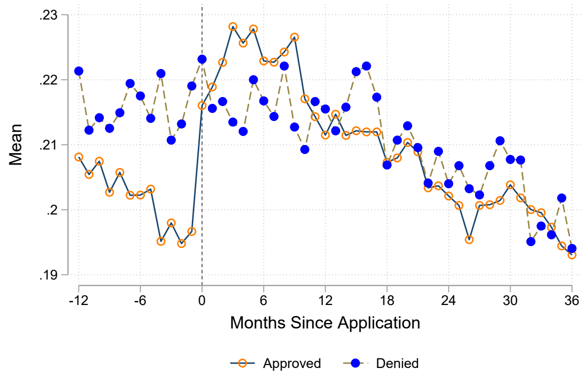
Note: This figure plots average outcomes around the time of application ($t = 0$) among the full set of applications, as opposed to only the EDP-reviewed applications used in the main text, separately for applicants that were approved and those that were denied. The outcomes in panels (a) and (b) are in 2002 CAD. The outcomes in the remaining panels are binary: panel (c) is receiving mental health treatment from a physician; panel (d) is visiting a general practitioner; panel (e) is being treated for a physical injury; panel (f) is being treated for a flu or respiratory illness.

B.6 Trends for Children

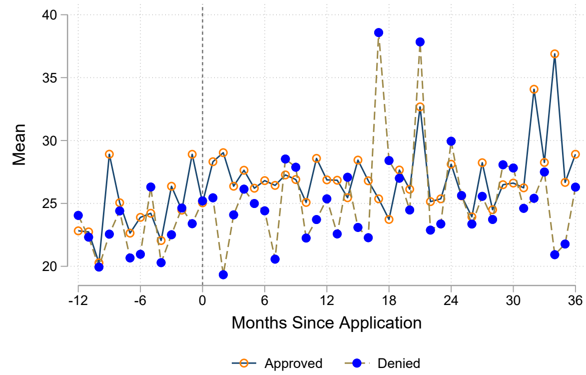
In this section, I plot trends in outcomes around the time of application for children aged 2 to 17 years at the time that their parent(s) applied for Income Assistance. A child is linked to their parents if the child is listed on the application. Unlike their parents, there is no pre-application spike in health spending. However, among children whose parents were approved for Income Assistance, pharmaceutical spending and GP visits increase, consistent with the pharmaceutical subsidy for Income Assistance driving increased consumption.

Figure B.8: **Universally-Insured Health Spending Around Time of Application, Children**

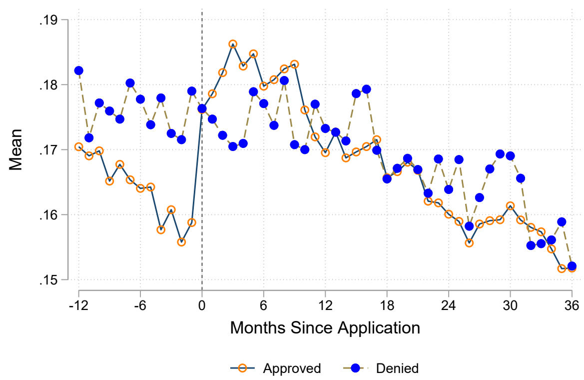
(a) **Probability of Receiving Medical Care**



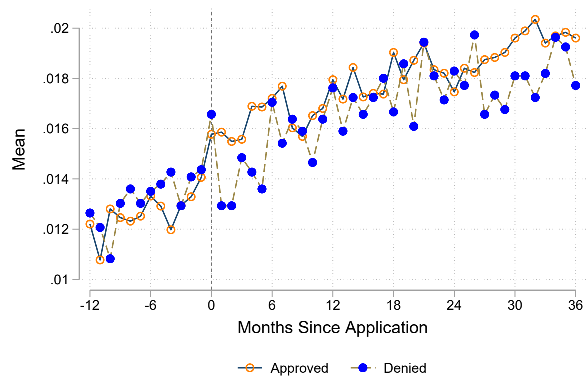
(b) **Hospital and Outpatient Spending**



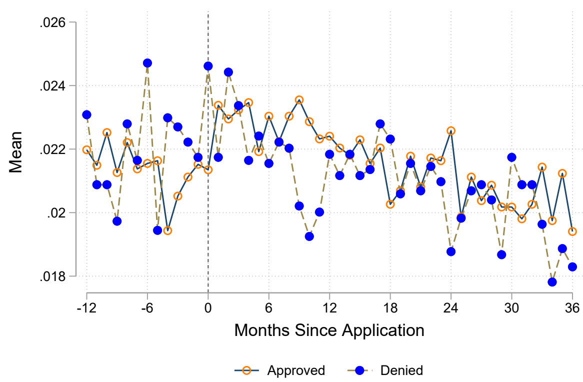
(c) **General Practitioner (GP) Visit**



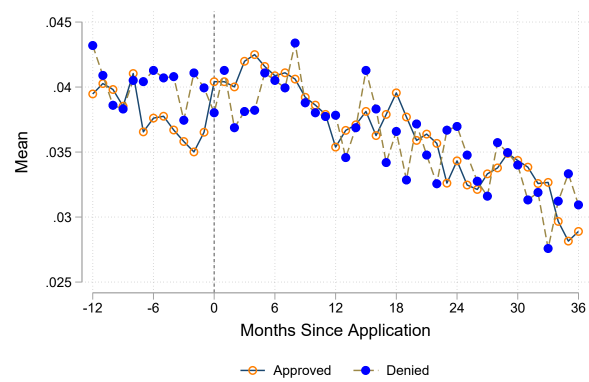
(d) **Mental Health Treatment**



(e) **Physical Injury**



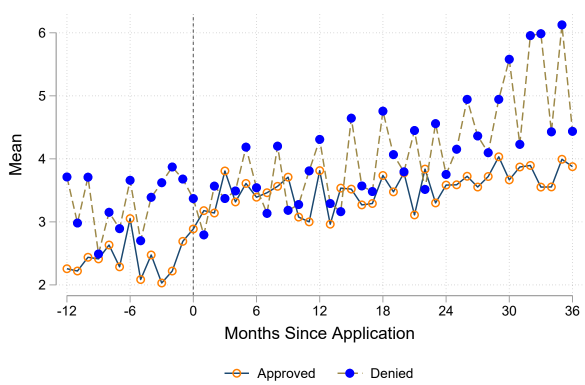
(f) **Respiratory and Flu**



Note: This figure plots average outcomes around the time of application ($t = 0$) among the set of EDP-reviewed applications, separately for applicants that were approved and those that were denied. The sample is children link to their parents' application. The outcomes in panels (a) and (b) are in 2002 CAD. The outcomes in the remaining panels are binary: panel (c) is receiving mental health treatment from a physician; panel (d) is visiting a general practitioner; panel (e) is being treated for a physical injury; panel (f) is being treated for flu or respiratory illness.

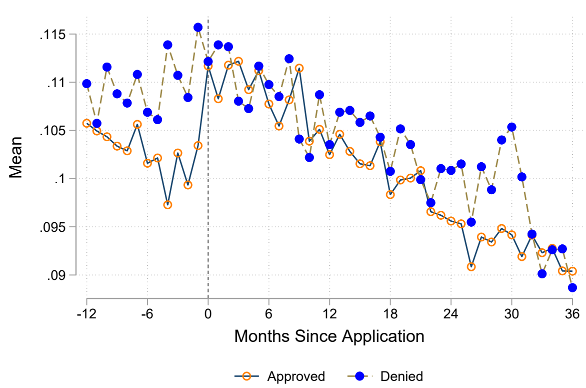
Figure B.9: **Pharmaceutical Spending Around Time of Application, Children**

(a) **Drug Costs**



(b) **Visited GP and Received Pharmaceutical**

(c) **Visited GP, Did Not Receive Pharmaceutical**



Note: This figure plots average outcomes around the time of application among the set of VO-reviewed applications, separately for applicants that were approved and those that were denied. The sample is children linked to their parents' application. The outcomes, in order, are average drug spending, whether the child visited a GP in the same month they filled a pharmaceutical prescription, and whether the child visited a GP without filling a prescription in that month.

B.7 Additional Results for the Causal Effects using VO Assignment

Table B.2: **Characterizing Compliers' Pre-Application Characteristics**

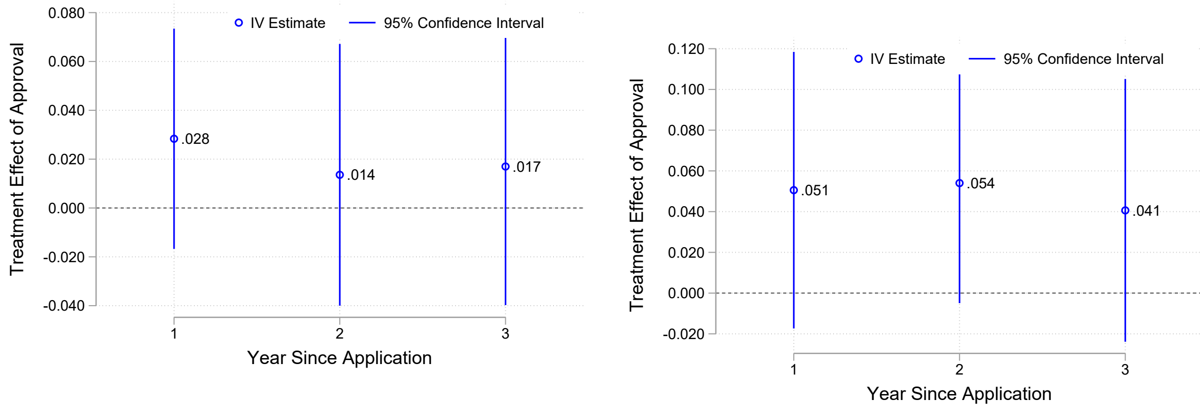
	Full Sample Mean	Complier Mean	Ratio	Z Value
Baseline Characteristics				
Age	34.69	33.53	0.97	1.01
Female	0.43	0.36	0.83	1.79
Childless Adult	0.53	0.65	1.22	2.41
Inferred Resident Before Application	0.89	0.90	1.01	0.38
No IA History	0.24	0.16	0.68	2.35
Spending Increase Before Application				
Received Any Medical Care 10-12 Months Before Application	0.41	0.33	0.80	1.92
Received Any Medical Care 1-2 Months Before Application	0.45	0.39	0.87	1.32
Medical Spending 10-12 Months Before Application	91.50	102.41	1.12	0.54
Medical Spending 1-2 Months Before Application	183.22	296.66	1.62	1.28
Cumulative Spending in 12 Months Before Application				
Total Non-Pharmaceutical Medical Spending	824.45	883.09	1.07	0.27
Mental Health Spending	74.71	78.09	1.05	0.16
Respiratory Illness Spending	7.72	5.31	0.69	1.39
Injury Spending	27.57	33.58	1.22	0.93
Spending on GP Visits	119.21	106.68	0.89	0.98
Pharmaceutical Spending	169.49	142.22	0.84	0.70
Pharmaceutical Spending Mental Health	53.68	43.90	0.82	0.59
Had Employer that Paid Insurance Premiums	0.12	0.08	0.67	1.50

Note: This table shows the average characteristics of the full sample in column (1), of compliers in column (2), their ratio in column (3), and the Z-statistic from the two-sided test of whether their ratio deviates from 1 in column (4). Spending variables are winsorized at the 99th percentile. Standard errors clustered at the adjudicator-year level.

Figure B.10: **Dynamic Treatment Effects on Disability Insurance and Excused from Work Benefits**

(a) **Disability Insurance Receipt**

(b) **Income Assistance Receipt, Excused from Work Search**

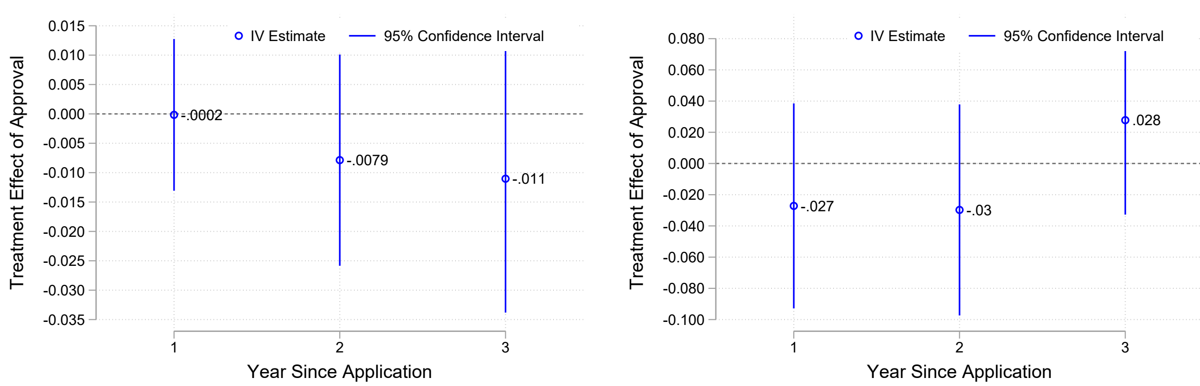


Note: These figures plot the estimates of the effect of application approval on the likelihood of receive disability insurance (panel(a)) and income assistance benefits in which the person is excused from work search requirements (panel(b)). 95% confidence intervals are shown. See main text for details.

Figure B.11: **Dynamic Treatment Effects on Mortality and Fertility**

(a) **Cumulative Death Probability**

(b) **Had Birth in Year**



Note: These figures plot the estimates of the effect of application approval on cumulative mortality and an indicator for giving birth in the year. The sample for the latter is restricted to women. 95% confidence intervals are shown. See main text for details.

C Details of Estimators

I follow the notes and notation of Kolesar (2013) in outlining the unbiased jacknife instrumental variable (UJIVE) estimator, and its comparison to 2SLS and the jacknife instrumental variable (JIVE). The model is:

$$Y_i = T_i\beta + W_i'\gamma + \epsilon_i \tag{C.1}$$

Where Y_i is the outcome, T_i is the endogenous variable, and W_i is a vector of controls. In my case, T_i is an indicator for person i's application being approved, and W_i contains office-by-year indicators.

Denote Z_i as a vector of instruments. In my case, Z_i is a $kx1$ vector of dummy variables equal to 1 if the application was reviewed by a given adjudicator, and k is the number of adjudicators. The 2SLS, JIVE, and UJIVE estimators can all be expressed in the same form:

$$\hat{\beta} = \frac{\hat{P}'Y}{\hat{P}'T} \tag{C.2}$$

where the difference lies in $\hat{P}'$:

$$\begin{aligned}
\hat{P}_{2SLS} &= H_{Z\perp}T \\
\hat{P}_{JIVE} &= M_W(I_n - D_{Z,W})^{-1}(H_{Z,W} - D_{Z,W})T \\
\hat{P}_{UJIVE} &= \Big[(I_n - D_{Z,W})^{-1}(H_{Z,W} - D_{Z,W}) - (I_n - D_W)^{-1}(H_W - D_W)\Big]T
\end{aligned}$$

The matrix H_Z is the projection matrix for Z, $Z(Z'Z)^{-1}Z'$, and $H_{Z\perp} = M_W H_Z$ where M_W is the annihilator matrix $I_n - H_W$. The matrix $H_{Z,W}$ is the projection matrix for the reduced form. Finally, $D_{Z,W}$ and D_W are diagonal matrices where the (i,i)th elements are the (i,i)th elements of $H_{Z,W}$ and H_Z, respectively.

β_{UJIVE} reduces bias relative to β_{JIVE} when the dimension of W is similar to the dimension of Z.

$\hat{P}$ in the three estimators are just different ways of projecting T onto the set of instruments. The 2SLS projects T onto adjudicator dummies after partialing out W. The JIVE does this on a leave-out-i basis. The UJIVE (i) projects T onto Z and W, (ii) projects T onto just W, then (iii) subtracts (ii) from (i), all on a leave-out-i basis.

My implementation deviates in one respect — rather than using T (the application approval outcome) in $\hat{P}$, I use the adjudicators' recommendation (R_i). See the main text for justification.