ESSAYS ON HEALTH AND DEVELOPMENT ECONOMICS

by

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DISSERTATION ABSTRACT

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This dissertation explores the impact of policy and economic conditions on the current economic crises of crime, substance abuse, and financial exclusion faced domestically and abroad. Although these issues span the income distribution, impoverished regions are disproportionately affected by the highest rates of risky behaviors such as drug abuse and crime. The ability for public policy makers to affect large populations of at-risk individuals can be difficult; oftentimes, these groups operate outside of the public sphere and large-scale interventions can miss the mark.

In my first substantive chapter, I investigate the efficacy of state-wide insurance reform aimed at reducing drug dependency by requiring insurance providers to cover rehabilitation and detoxification. Utilizing state-level panel data in a generalized differences-in-differences framework, I find that states which enact laws expanding insurance coverage are successful at encouraging treatments for some types of conditions but are limited in their ability to reach individuals struggling with opiate addiction and, correspondingly, have little impact on deterring accidental overdose deaths.

In my second substantive chapter, I question the assumptions made in previous empirical work regarding the relationship between economic conditions and crime. Existing literature finds that property crime rates are positively correlated with the unemployment rate. In this paper, I investigate whether this relationship is evolving over time and find that the relationship between property crime rates and unemployment has diminished toward zero. Moreover, I find evidence that there is a non-zero relationship between unemployment and violent crimes during certain periods in time.

In my last substantive chapter, we develop a theoretical model illustrating the basic trade-offs in the functioning of financial institutions (Village and Savings Loan Associations) designed to provide financial inclusion to under-served populations in developing countries. We develop a theoretical model which suggests that these groups lack a mechanism to ensure equilibrium in the supply and demand for funds. We test the predictions of this model using experimental data from newly formed groups in Uganda and find that groups operate with excess demand for loans but are often able to generate a high return on savings.

This dissertation includes previously unpublished co-authored material.

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For my daughter, Emma Grace Selby.

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CHAPTER I

INTRODUCTION

Public policy geared towards improving welfare of at-risk populations in both developing and developed countries is both necessary and challenging. In the United States, the opioid drug empidemic has claimed the lives of over 33,000 individuals in 2015 and the drug overdose death rate has been rising at an alarming rate over the last several decades. Crime also continues to be an issue, particularly in impoverished regions in the country. In developing countries, poorer rural regions often struggle to meet basic needs and are particularly sensitive to environmental shocks such as droughts or floods.

Policy makers have long sought out large-scale policies or reforms to help improve the outcomes for these vulnerable populations. However, because many of these groups operate outside of the public sphere, large scale interventions may be limited in effectiveness; thus, a rigorous analysis of the impact of interventions is warranted. In this dissertation, I investigate the impact of state health care reform on drug abuse, revisit and question the established relationship between unemployment and crime, and explore the functioning of savings groups established by non-governmental organizations in Uganda.

One of the most pressing concerns in the United States has been the identification of interventions that can successfully mitigate the continuous rise in opiate-related fatalities. In Chapter II, I estimate the impact of state legislative insurance mandates which increase coverage for rehabilitation and detoxification services for the treatment of addictive disorders. Using text from state legislative acts, I exploit the variation in timing of enactment of laws across states in a generalized differences-in-difference model to identify the causal impact on admissions into treatment and accidental drug overdose deaths. I find that laws encourage admission into substance abuse treatment, primarily for alcohol and marijuana, but that they are less successful at attracting admissions into programs to treat opiate addiction. Correspondingly, I find limited evidence that laws have a significant impact on the accidental drug overdose rate.

In Chapter III, I provide an empirically rigorous exercise to challenge assumptions regarding the time-stability of the impact of economic conditions on crime rates. Previous literature has consistently identified a positive relationship between unemployment and property crime and little to no impact on violent crime rates. The empirical work assumes that parameters are consistent over time and thus exogenous to external factors. This assumption, though convenient, is likely invalid because the individual's choice to commit crime is dependent on factors that affect the return to crime and the probability of apprehension (Becker, 1968). In this paper, I explore whether the relationship between unemployment and crime has changed over time and I find evidence that, for property crimes, the parameter has diminished toward zero during recent years. I also find evidence of non-zero impacts of economic conditions on violent crimes during some periods in time. This highlights the need for further research on the topic and suggests that policy makers should take caution in the assumption that economic downturns will drive up crime rates.

Chapter IV is coauthored with Alfredo Burlando (University of Oregon) and Andrea Canidio (INSEAD). In this paper, we examine the pressing concern in developing countries to increase financial inclusion for under-served communities. Non-governmental organizations (NGOs) helped to guide the formation of local groups called Village Savings and Loan Associates (or savings groups) which provide small-scale banking for vulnerable populations. Savings groups operate in many ways as micro-credit unions where involved members save funds in a group pot and funds are distributed out in the form of short-term loans which are repaid with interest. In this paper, we develop a theoretical model of the functioning within these groups and and a primary conclusion is that groups lack a mechanism to ensure the supply and demand for funds are equal. We test the predictions from this model using administrative data from newly formed Ugandan savings groups and find that groups are typically rationing available funds yet are able to generate a high return to savings. This is indicative that these groups are providing a valuable resource to the communities but that there exist welfare-improving changes to policies on group formation and operation.

Taken together, this dissertation highlights three important items. Firstly, policy interventions, such as large scale insurance reform, may have measurable benefits on reducing risky behavior but may miss the most at-risk groups by design. These policies are a type of "one-size-fits-all" intervention, which may be inappropriate given the socioeconomic and demographic heterogeneity between individuals in the target population. Secondly, policy implications arising from literature connecting increased crime rates to changes in unemployment may be off target as the relationship between these measures is likely endogenous to other factors. Lastly, financial inclusion of poor populations in developing countries is improved by the establishment of savings groups. Groups are able to generate a high rate of return to savings and can obtain funds during periods of need; however, there is evidence of sub-optimal group behavior. In all three cases, there is reason to believe that problematic economic outcomes can be improved through policy but that careful consideration of the limitations will help to make programs more successful in the future.

CHAPTER II

THE IMPACT OF SUBSTANCE ABUSE INSURANCE MANDATES

Introduction

Drug-related mortality has been consistently increasing in the United States over the last several decades. In 1999, there were fewer than five accidental overdose deaths per 100,000 population and, by 2015, this number surpassed thirteen per 100,000 population. A major component to this rise has been increased usage of opioids (such as prescription pain medication) and opiates (such as heroin) and in more recent years the availability of highly potent pain management drugs like Fentanyl.

Many strategies exist to reduce this mortality rate. At the most basic, drug related deaths can be reduced by preventing drug use and access, improving the health and safety of drug users, or by treating addiction through rehabilitation, detoxification, and therapy. Prevention policies, such as Prescription Drug Monitoring Programs, can reduce drug use by increasing scarcity of drugs.[1] However, these policies may have a limited effect for individuals with severe dependency to substances (and thus on the margin for overdose) as abrupt changes to use can be life-threatening. Facilities devoted to the treatment of addiction, such as rehabilitation and detoxification, can provide a safe environment for reducing drug use and provide addicts with a skill set for continued sobriety after treatment concludes.

Since as early as 1975, states have been enacting laws which require insurance providers to include or increase benefits for substance abuse treatment (SAT). These laws are designed to expand coverage for addiction by decreasing the out-of-pocket cost

[1] Prescription Drug Monitoring Programs aim to reduce access to drugs by creating a centralized information system of drug prescription histories to be used by medical professionals.

to individuals requiring treatment thus encouraging individuals enter into treatment. SAT can be prohibitively expensive, with basic services starting at around $1,000, many individuals without insurance coverage for treatment who develop an addiction would opt out of treatment. These high costs increase the probability of continued drug use and overdose death and other complications of heavy drug use.[2]

In this paper, I examine the effectiveness of state health mandates requiring SAT benefits to be included in insurance policies. Using panel-data empirical methods, I estimate the impact of these mandates on SAT admission rates into detoxification and rehabilitation programs. I also estimate the effect of these policies on accidental drug mortality rates. I further investigate the heterogeneous impacts of law implementation on admission rates by primary drug concern, source of referral for treatment, and treatment setting.

I find that states which enact legislation experience an increase in admissions into SAT programs of 13 to 25 percent. The increase is driven surprisingly by alcohol, amphetamines[3] and marijuana treatments; I find no evidence of increases in admissions for hallucinogens, opiates[4] or sedatives and tranquilizers. Rates of admission do not vary by referral source, suggesting that mandates are both providing benefits for the person on margin of receiving treatment as well as individuals with an unrealized demand for services.[5] Moreover, admissions into both inpatient and outpatient settings, as well as

[2]Common conditions include aortic stiffening, arrhythmia, coronary heart disease, brain hemorrhages, Hepatitis, HIV, and infection.

[3]Primarily methamphetamine ("meth").

[4]"Opiates" in this paper are defined as opioids (such as prescription pain medication like OxyContin, methadone, and other synthetics) or opiates, (such as opium, heroin, morphine, and other natural opium derivatives). The remainder of the paper will aggregate opiates and opioids into the term opiates, acknowledging heterogeneity within this count.

[5]This can include, but is not limited to, individuals who receive sentences for DUI/DWI, use substances but do not currently have or recognize a dependency, and individuals who may develop an addiction following long-term use of prescription medication due to a medical condition.

rehabilitation and detoxification, increase at a similar rate following the legislation. This is indicative that the laws are not exclusively encouraging individuals to seek higher cost services, such as inpatient therapy, but rather that individuals are seeking treatment based on their needs.

Lastly, I examine the effect that laws increasing SAT benefits have on accidental drug overdose death (OD) rates. I find limited evidence that drug-induced mortality decreased in states which enacted mandates. This is consistent with the finding that admissions into treatment for opiate addictions did not increase significantly following the enactment of the mandates. However, when controlling for state insurance mandates increasing coverage for treatment of mental illness (excluding addictive disorders), I find that the accidental drug OD rate decreased by about 14 percent in states with either type of law enacted. This suggests that treatment from practitioners, in general, can help to reduce overdose deaths.

This paper contributes to the literature investigating the impact of policies on accidental drug mortality. Papers examining prevention programs have largely focused on Prescription Drug Monitoring Programs (PDMP). The effectiveness of these policies are mixed. Paulozzi et al. (2011) find that PDMPs do not significantly decrease drug overdose or consumption of opiates, whereas Reifler et al. (2012) shows that PDMPs were associated with a significant decrease in accidental drug poisoning reported to the Poison Control Center and an increase in substance abuse treatment admissions. There is also a small literature investigating the impact of education and effectiveness of rescue medication (primarily naloxone). In particular, Walley et al. (2013) finds that a Massachussetts overdose education and nasal naloxone distribution program, which educated opiate users of ways to identify overdose and how to administer the rescue medicine, decreases opioid-driven death rates. Lastly, there are few economic papers investigating the impact of SAT on drug mortality. Swensen (2015) finds that increases in SAT facilities significantly decreases the drug overdose death rate by increasing access to care. In my paper, I provide the complementary demand-side analysis investigating the impact of a policy designed to encourage treatment uptake.

There is also a small literature which examines the impact of state insurance legislation on substance abuse and other risky behavior. Lang (2013) investigates the impact of mental health insurance laws on suicide rates and finds that suicides significantly decline following enactment. Fernandez and Lang (2015) find that the decrease in suicide rate corresponds to a decrease in available organs for donation. Dave and Mukerjee (2011) examines the impact of mental health insurance mandates on uptake of rehabiliation and detoxification services and find evidence the laws have a positive impact on treatment. Lastly, Klick and Stratmann (2006) find that states which pass mental health laws that explicitly include substance abuse disorders see increases in alcohol consumption. In contrast, I identify laws which affects substance abuse insurance coverage directly, regardless of whether it has an impact on other mental health conditions. In addition, I investigate the extent of the impact on admissions on accidental overdose. Lastly, my heterogeneity analysis provides new insights on the mechanisms behind the mandates.

This rest of this paper is structured as follows. First, I discuss the background of substance abuse treatment and overdose in the United States, provide a detailed explanation of laws in this analysis, and further discuss related literature on the impact of insurance laws. I then describe the empirical models used in this paper and discuss the data used in this paper. Following this, I report the results of this investigation and conclude.

Background

Drug Use and Treatment in the United States

Accidental drug deaths make up the majority of drug-related mortality in the United States.[6] Intentional drug deaths (i.e. drug deaths from suicide or homicide) and deaths where the intent is unknown make up the residual. Figure 1 illustrates the trends in accidental, suicidal, and unknown intent drug death rates between 1999 and 2015. While there has been little observable change in drug-related suicide over this period, there has been large increases in the accidental drug death rate with 11,155 deaths occurring in 1999 to well over 44,126 in 2015. This corresponds to less than four accidental drug deaths per 100,000 population to more than thirteen per 100,000, respectively.[7]. This three-fold increase is primarily driven by increases in narcotic deaths and deaths where the drug is unspecified.[8] On average there were 3.9 deaths per 100,000 population with underling cause of death was due to an unspecified drug. Of these, these 2.4 deaths had narcotics found during autopsy.[9] The trends in death rates to non-narcotic other drugs[10] experienced little change over this time period (see Figure 2).

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[6]Drug-related mortality includes deaths where the cause of death was deemed to be "poisoning by and exposure to noxious substances" (World Health Organization (1992)). For the purposes of this paper, I exclude deaths due to alcohol, organic solvents, halogenated hydrocarbons, other gases and vapors, and pesticides.

[7]Data accessed from CDC Wonder at http://wonder.cdc.gov on 05/19/2016. International Classification of Diseases Codes 9th Revision (ICD-9) include E850-E858 for years 1990-1998, and ICD-10 codes X40-X44 for years 1999-2014.

[8]ICD-10 codes for narcotics and unspecified other drugs is "X42" and "X44", respectively.

[9]Multiple cause of death data includes up to twenty causes of death. The presences of narcotics is coded as "T40" in these sections.

[10]These include nonopioid analgesics, antipyretics antirheumatics, antiepileptic, sedative-hypnotic, antiparkinsonism, psychotropic drugs, and other drugs acting on the autonomic nervous system (ICD-10 codes "X40," "X41", "X43").

FIGURE 1. Drug Deaths by External Cause

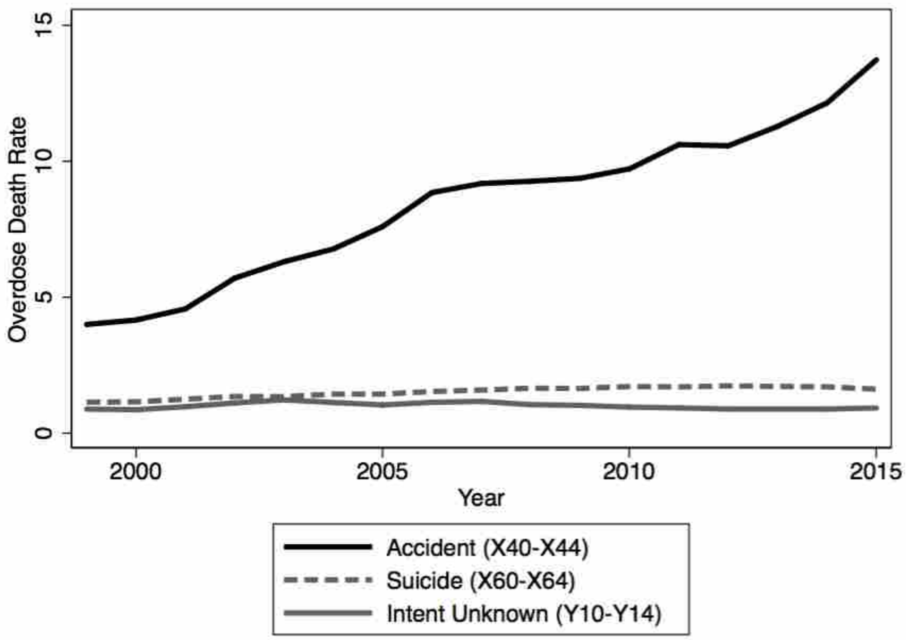
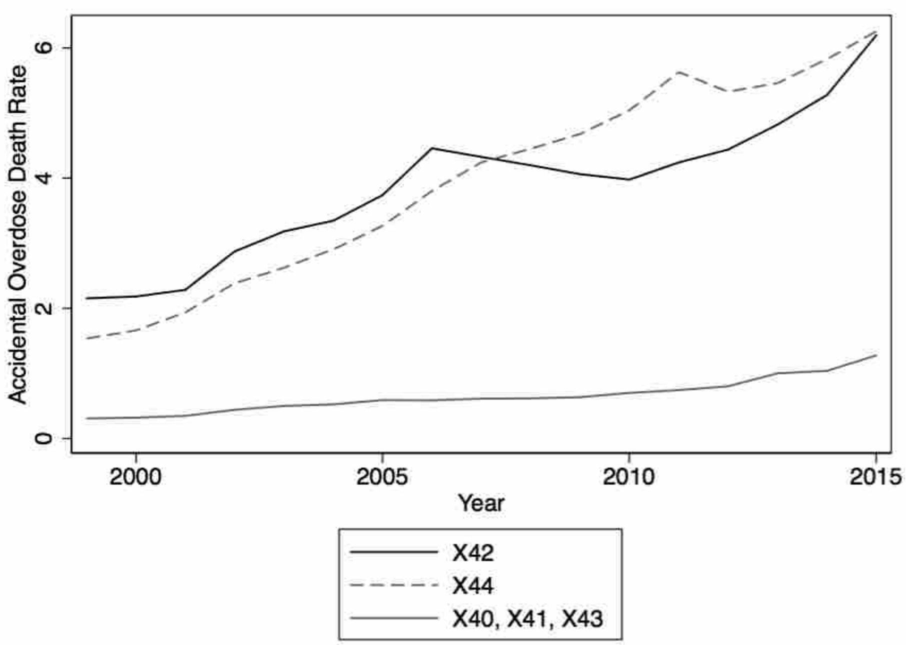
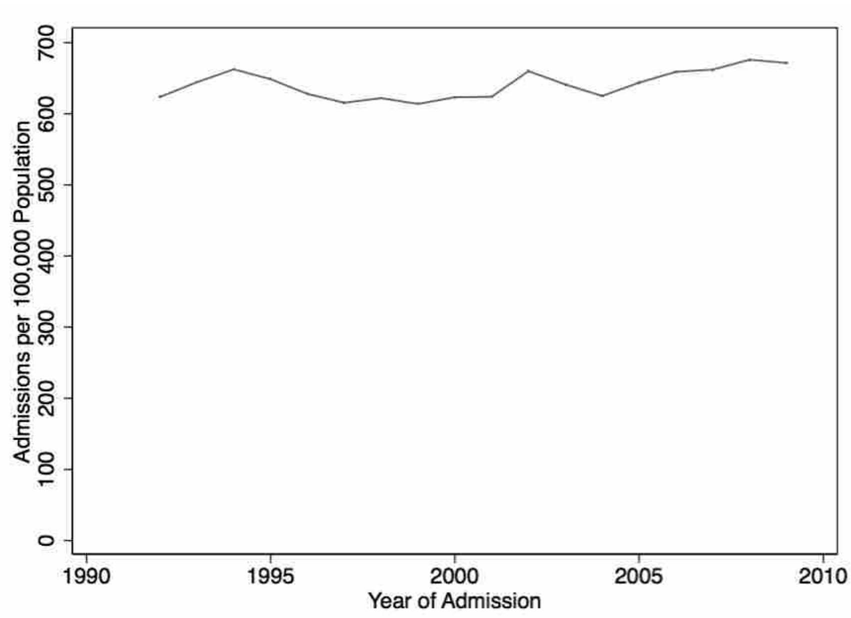


FIGURE 2. Accidental Drug Death Rates by ICD Code



Figures 3 and 4a-4h illustrate the change SAT admission rates (admissions per 100,000 population) for general admissions and by primary drug concern, respectively, between 1990 and 2009. There is no clear upward trend in treatment admission rates, on average, with yearly variation around the mean 650 admissions per 100,000 population. Admissions reporting alcohol or cocaine as their primary concern have been declining since 1992. For alcohol, treatments decreased from a high of over 350 to as low as 250 per 100,000 population. On the contrary, admissions reporting marijuana, opiates, or sedatives and tranquilizers have been generally increasing over the period. The rise in opiate and sedative admissions has been about two-fold and increase in marijuana treatment admissions has been nearly three-fold.[11] Treatment rates for hallucinogens and other drugs[12] did not increase or decrease systematically over the period.

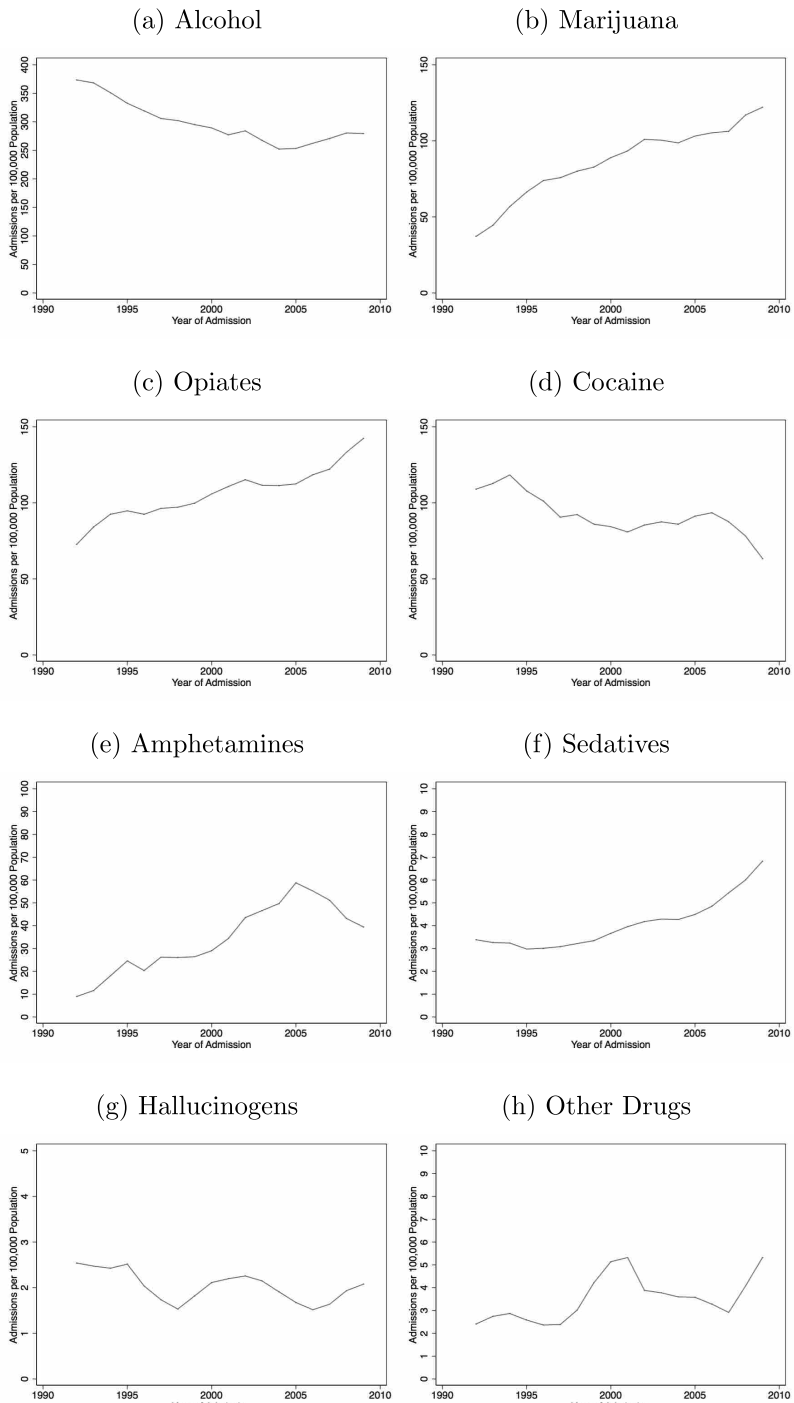
FIGURE 3. Treatments per 100,000 Population



[11]Marijuana categorized as a Schedule I controlled substance and during this time period was illegal under all state and federal law for recreational use. During this time, several states had passed legislation to allow for medicinal marijuana use, but it remains illegal under federal law as of the date of this paper.

[12]Includes inhalants and over-the-counter medication.

FIGURE 4. Treatment Admission Incidence Rates by Primary Drug Concern



SAT Insurance Mandates

Over the course of thirty years, states have enacted legislation requiring insurance providers to increase coverage for treatment of substance abuse disorders. Table 1 includes the enactment date and scope of law (discussed in the next subsection) for each state. By 2007, forty-two states had enacted a substance abuse insurance mandate and the majority of laws were passed between 1990 and 2002. The laws were most often targeted at large group health plans and often made exemptions for small group health plans.[13] Typically, mandates includes language which explicitly requires insurers to provide or offer coverage for SAT, details the level of benefits that must be covered, discusses whether treatment for other mental illness is subject to the law, and the effective implementation date of a law.

The following subsections discuss heterogeneity in substance abuse insurance mandates as well as laws passed at the federal level.

Scope of Benefits Insurances laws can vary on the generosity and scope of mandated benefits from state to state. For example, mandates may include explicit language requiring that all new plans provide benefits if they had not done so before. Additionally, the mandates may differ on the level of the benefits that must be provided when offered. "Parity" laws are among the most generous, and require all new plans to include benefits for SAT and that these benefits must be "no more restrictive" than for physical health. "Minimum Mandated Benefit" (MMB) laws are slightly less generous; they require the inclusion of SAT benefits in plans but allow lower coverage than benefits for physical conditions. Lastly, "Mandated if Offered" (MIO) laws do not have explicit language requiring benefits for treatment. However, plans including SAT benefits must meet some minimum benefit level. While investigating the scope of benefits is not the primary focus

[13]The justification here is to avoid increasing premiums. Providers were also exempt if they could show that the inclusion of benefits would increase premiums more than a minimum threshold.

TABLE 1. State Substance Abuse Legislation

State	Effective Date	Scope	State (cont.)	Effective Date	Scope
Mississippi*	January 1, 1975	MMB	Minnesota	August 1, 1995	MIO
New Hampshire	January 1, 1975	Parity	Massachusetts	January 1, 1996	MMB
New Jersey	January 1, 1975	Parity	Montana	January 1, 1997	MMB
Wisconsin	May 5, 1976	MIO	Kansas	January 1, 1998	MMB
Nevada*	January 1, 1979	MMB	Vermont	January 1, 1998	Parity
Ohio*	January 1, 1979	MMB	Georgia	July 1, 1998	Parity
South Dakota*	July 1, 1979	MMB	New York	January 1, 1999	Parity
Oregon*	January 1, 1981	MMB	Connecticut	January 1, 2000	Parity
Michigan	January 1, 1982	MMB	Missouri	January 1, 2000	MIO
Tennessee	January 1, 1982	Parity	Montana	January 1, 2000	Parity
Maine	January 1, 1983	MIO	Oregon	January 1, 2000	MMB
New Mexico*	January 1, 1984	MMB	Virginia	January 1, 2000	Parity
North Carolina	January 1, 1985	Parity	Massachusetts	July 1, 2000	Parity
North Dakota	January 1, 1985	MMB	Kentucky	July 14, 2000	MIO
Arkansas	November 17, 1987	Parity	Delaware	July 18, 2001	Parity
Hawaii	January 1, 1988	MMB	Rhode Island	January 1, 2002	Parity
Washington	January 1, 1988	MMB	Colorado	January 1, 2003	MMB
Nebraska*	January 1, 1989	MMB	West Virginia	January 1, 2003	Parity
California*	January 1, 1990	MMB	Indiana	July 1, 2003	MIO
Pennsylvania	January 1, 1990	MMB	Maine	January 1, 2004	Parity
Missouri	July 10, 1991	MIO	Alaska	July 1, 2004	MIO
Florida	January 1, 1993	MMB	Texas	April 1, 2005	Parity
South Carolina	January 1, 1994	MMB	Oregon	January 1, 2007	Parity
Utah	January 1, 1994	MMB	Louisana	January 1, 2009	MMB
Colorado*	July 1, 1994	MMB	Kansas	July 1, 2009	Parity
Maryland	July 1, 1995	Parity	Wisconsin*	April 29, 2010	MIO

Notes:
* *Only affects benefits for alcoholism*
Source: WestLaw and HeinOnline

of my paper, I investigate whether the results of the analysis are robust to breakdown by type of law.

Health Legislation State legislatures often address substance abuse treatment insurance coverage as a part of a comprehensive bill where addictive disorders are categorized as a mental illness. However, several states enacted mental health laws which explicitly excluded substance abuse disorders and other states which enacted SAT laws without affecting other benefits. In addition, occasionally states amend an existing mental health bill to include substance abuse disorders years after the original enactment date.

For the majority of this paper, I focus on laws which affect SAT benefits regardless of whether it was packaged as part of a mental health law or passed alone. However, there exists the possibility of spillovers from increasing mental health treatment onto substance abuse treatment (such as referrals). Laws which increase benefits for mental health treatment - excluding SAT - are also occasionally passed around the same time as other laws which do increase SAT. To check for this potential endogeneity, I include other mental health mandates in some specifications.

Federal Mandates Congress passed the Mental Health Parity and Addiction Equity Act (MHPAEA) of 2008 which mandates that insurers provide benefits for SAT, as well as other mental illness treatment, at parity with physical health in all plans which already included benefits; however, this law did not require plans to offer or include benefits (a MIO law). [14] In this paper, I focus on the impact of laws enacted at the state level before the implementation of the MHPAEA.

Literature on Health Reform Policy

Previous literature has focused largely on the impact of legislation affecting coverage for mental illness on treatments for mental disorders and suicide. A small set of papers focus on substance abuse or substance abuse treatment, but do so through the lens of mental health.

There has been mixed evidence in previous literature on the effectiveness of insurance mandates in encouraging treatments for mental illness. Harris et al. (2006) used quasi-experimental techniques to estimate the impact of mental health insurance reform

[14] Later, the Patient Protection and Affordable Care Act (ACA) in 2010 extended on the MHPAEA by mandating all plans - including individual, HMO, and Medicaid/Medicare - to provide benefits in all plans and that discrimination based on preexisting conditions could not be allowed. The ACA forced all state laws to switch from MIO or MMB to full parity as well as provided insurance to over twenty million previously uninsured individuals.

on mental health care utilization and found that mental health parity laws significantly increase the probability of receiving treatment. Barry and Busch (2008b) find that mental health parity laws are effective at increasing services for mental illness for people with severe conditions and those who are of lower socioeconomic status. In their related paper, Barry and Busch (2008a) find no evidence that these policies increased treatment rates for children. Lastly, Bilaver and Jordan (2013) finds limited evidence for the effectiveness of these laws on treatment for Autism Spectrum Disorder.

There have been several papers investigating the role of mental health insurance laws on suicidal behavior. Suicide is strongly associated with severe mental illness and increasing mental health insurance coverage can increase the likelihood of receiving treatment before it manifests into suicidal behavior. Klick and Markowitz (2006) used ordinary least squares and two-stage least square over a long panel of state suicide data and found no evidence that a mental health parity law decreases the suicide rate. In contrast, Lang (2013) and Fernandez and Lang (2015) find that parity laws are both effective at reducing suicide rates but that there is a spillover onto availability of available organs for donation.

To date, there is no paper which exclusively focuses on mandates pertaining to substance abuse treatment. However, there are a few papers which examine differential impacts of mental health insurance mandates which include or exclude substance abuse disorders. Dave and Mukerjee (2011) create three categories for insurance mandates: the first is a broad spectrum mental illness law which includes substance abuse and has little to no exceptions, the second is a limited law which has limitations on certain coverages, and the third being a weak law which allows exceptions for substance abuse. In this study, they use a Poisson panel regression model and find that broad spectrum parity laws are effective at increasing substance abuse admissions. Klick and Stratmann

(2006) categorize mental health insurance laws as explicitly including substance abuse, not explicitly excluding substance abuse, and explicitly excluding substance abuse and find that beer consumption increases if the law was a parity law that included alcohol dependency benefits.

Empirical Methodology

Substance abuse insurance laws may affect demand for services by covering previously uninsured individuals or by increasing the amount of services beneficiaries undertake (extensive and intensive margin, respectively). However, if the laws increase premiums[15] then we may see fewer treatments following the laws. Further, treatment may influence current and future drug use and alter the probability of dying due to accidental overdose. However, there may be the reverse effect if individuals experience rational addiction,[16] or if SAT is increasing access to addictive substances.[17]

In order to identify the effect of insurance mandates on the SAT admission and OD incidence rates, I exploit the timing of laws in different states. I define the vector of indicator variables $\vec{L}_{st}$ for SAT insurance mandates laws, each taking on the value of one in state s for all years on or after the effective year of the law and zero in previous years. I then estimate the following log-linear model:

$$log(Y_{st}) = \beta_0 + \beta L_{st} + \Gamma X_{st} + \delta_s + \alpha_t + \Omega_s * t + u_{st} \tag{2.1}$$

[15] The concern here is that as more at risk people are added to the insurance risk pool, insurance premiums inflate. When this drives healthy people out of the risk pool, this is called a "death spiral". This is unlikely in these laws because of exemptions if it can be shown that premiums are likely to increase substantially.

[16] That is, by reducing the cost of consuming drugs (i.e. the cost of treating addiction in the future) individuals will increase their consumption in the present.

[17] Prescription methadone, in particular, is a highly abused substance and is made available through treatment for opiate addiction.

where Y_{st} is the incidence rate of SAT admissions or OD in state s at time t, X_{st} includes the unemployment rate, Medicaid and Medicare expenditures per capita, household income per capita, and demographic characteristics, δ and α are state and year fixed effects, Ω_s is a vector of state specific time trends (included in some specifications), and ϵ_{st} is an independent and identically distributed mean error term.

Interpretation of Estimates The null hypothesis is that $\beta = 0$, or that there is no observable difference in SAT admission or OD rate in states following the enactment of a law relative to having no law in place. Rejection of the null would imply that states which switch from no law to having a law in place have a geometric average incidence rate which is $100*(e^{\beta}-1)$ percent different than the geometric average with no law enacted. For small β, the estimated coefficient is similar in magnitude to this percent.

Identification There assumptions needed to identify causal effects in this model are that states that enact laws have common trends in SAT and OD rates with states that do not in absence of legislation and that state legislators are not endogenously enacting mandates in response to generally worsening conditions in SAT or OD.

States certainly have heterogeneous trends in both measures due to differences in other laws, preferences, and access to substances. However, the inclusion of state fixed effects and state specific time trends help to correct for this issue. The matter of endogenous enactment of laws is thus the primary concern and is reasonable considering the motivations leading to propositions of SAT insurance reform. To check for this, I perform an event-study which examines trends pre- and post-enactment. Trends prior to enactment which show SAT rates decreasing or OD rates increases just prior to the enactment date would create a concern that law makers are responding to these conditions.

Data Description

SAT admission statistics come from the Treatment Episode Data Set for Admissions (TEDS-A).[18] The TEDS system collects administrative data on each admission into facilities and is comprised of mainly providers that receive public funds (e.g. Federal Block Grant) to provide substance abuse treatment. There are also some institutions that do not receive these funds that submit their data as well. This data is available from 1992 to 2012 and the survey questions is consistent across the years.[19] One primary data limitation is the inability to distinguish between unique individuals rather than admissions. In the same survey year, a single individual may be reported more than once if they were admitted into a treatment program on more than one occasion. Thus, the calculated incidence rate in this paper will be capturing service utilization rather than the percentage of the population receiving treatment.

Data for drug-related overdose deaths comes from the Multiple Cause of Death (MCD) files from the CDC's National Center for Health Statistics. Spanning back to 1968, the MCD provides individual level data on the manner and place of death, the decedent's demographic and socioeconomic characteristics, and an array of information about co-occurring conditions and toxicology results. I focus on deaths that are deemed to be accidental and due to poisoning from drugs (excluding alcohol). For years 1990 to 1998, these are coded using the International Classification of Diseases, Version 9 (ICD-9) as E850-E858. For years 1999 and forward, cause of death are coded as X40-X44 (ICD-10).

In order to construct incidence rates, I utilize state-level population data from the Surveillance, Epidemiology, and End Results Program (SEER) funded by the National

[18] Obtained from Substance Abuse and Mental Health Services Administration (2014).

[19] While mostly balanced, there are some states in some years that are not included in TEDS-A (about three percent of observations) due to reporting issues.

Cancer Institute. The SEER data set provides a modification of the Census Bureau's intercensal estimates and the county population estimates produced by the the Census Bureau's Population Estimates Program and also accounts for population changes following Hurricane Katrina and Rita. State-level population is also decomposed by race and single year ages. This data is also used to create state level demographic indicators, such as percent of the population that is white, black, and in various age groups.

In addition to demographic characteristics, my analysis uses the Bureau of Labor Statistics Local Area Unemployment Statistics estimate of the state level unemployment rate, the Bureau of Economic Analysis estimate per capita income, and Medicaid and Medicare health expenditures per capita (calculated using data from the Center for Medicaid and Medicare Services and SEER population data).[20] The unemployment rate and income per capita are utilized to control for economic conditions that may influence drug use. Medicaid and Medicare expenditures controls from contemporaneous welfare systems that may affect health costs of individuals in these markets.

Summary Statistics

Table 2 reports summary statistics for the data used in this analysis between 1992 and 2008. There were on average 640 admissions per 100,000 population into substance abuse treatment between 1992 and 2009. The top reported concerns at admission were for alcohol, opiates[21], cocaine, and marijuana. Approximately 62 percent of admissions were into an outpatient program and 76 percent were into rehabilitation programs. Over two-thirds of all admissions into treatment were from self-referrals and referrals

[20] This number does not reflect expenditures per enrollee. Rather it reflects the size of the health welfare system in the state.

[21] "Opiates" include heroin, non-prescription methadone, and other opiates and synthetics.

from the courts and criminal justice system[22] with 213.3 and 218.6 admissions per 100,000 population, respectively. Second to these are referrals from other health care providers[23] and community referrals[24] (116.6 and 72.1 admissions per 100,000 population, respectively). Lastly, there was an average of about 5.4 accidental ODs per 100,000 population.

Control variables include state unemployment rates, per capita real income, real Medicaid and Medicare expenditures per capita, and state demographics. The unemployment rate averaged about 5.4 percent and income per capita was about $36,880 in 2009 dollars. States had an average annual $1,730 and $2,140 per capita expenditures on Medicaid and Medicare, respectively. About fifty-one percent of the population was female, seventy percent white (non-Hispanic), thirteen percent black, fourteen percent were between the ages of fifteen and twenty-four, fourteen percent between the ages of twenty-five and thirty-four, thirty percent between the ages of thirty-five and fifty-four, and thirty-percent older than age fifty-four.

Results

SAT Admissions

Table 3 reports the main results for the impact of substance abuse insurance legislation on the SAT incidence rate. Columns (1) and (2) include estimates for univariate and multivariate OLS with controls for socioeconomic and demographic conditions, respectively. While insignificant, the coefficient on the dummy variable for the SAT

[22]Court referrals include DUI/DWI, deferred prosecution requirements, pretrial release, or before/after judicial adjudication.

[23]Includes alcohol/drug abuse care providers, mental health providers, physical health providers, hospital, and other licensed health care specialists.

[24]Includes schools, employers, and other community referrals such as shelters, unemployment assistance, defense attorneys, and self-help groups like Alcoholics/Narcotics Anonymous.

TABLE 2. Summary Statistics for Substance Abuse Treatment, Overdose Rates, and Controls

	Mean	SD	Min	Max	N
Dependent Variables					
Admission Rate	639.98	375.84	46.91	2017.92	822
Admissions by Primary Concern:					
Alcohol	296.88	236.35	23.12	1553.14	822
Cocaine	93.05	57.38	1.87	279.94	822
Marijuana	85.62	51.9	9.23	315.66	822
Opiates	105.08	120.57	1.24	651.79	822
Hallucinogens	2.01	1.87	0	18.71	822
Amphetamines	34.65	53.97	0.07	278.84	822
Sedatives/Tranquilizers	3.97	3.11	0.12	22.3	822
Other Drugs	3.45	5.75	0.14	83.2	822
Admissions by Setting:					
Inpatient	243.69	224.32	0	1389.78	822
Outpatient	396.19	220.64	0	1634.92	822
Rehabiliation	487.83	269.91	0	1506.53	822
Detoxification	152.06	182.99	0	1288.39	822
Admissions by Referral Source:					
Self	213.33	151.88	0	816.94	822
Community	72.06	56.28	0	468.43	822
Health Care System	116.61	116.76	0	721.28	822
Crim. Justice System	218.6	146.62	0	1354.69	822
Overdose Death Rate	5.39	3.36	0.1	22.48	850
Control Variables					
Unemployment Rate	5.37	1.34	2.3	11.3	850
Income per Capita	36.88	5.56	22.65	57.55	850
Medicaid per Capita	1.73	0.76	0.63	4.77	850
Medicare per Capita	2.14	0.56	0.49	3.98	850
% Female	0.51	0.01	0.47	0.52	850
% White (non-hispanic)	70.03	14.24	21.62	98.08	850
% Black	12.92	7.85	0.28	37.42	850
% Age 15-24	14.31	0.94	11.87	20.05	850
% Age 25-34	13.95	1.08	10.87	18.33	850
% Age 35-44	15.19	1.59	11.39	21.45	850
% Age 45-54	14.75	0.87	11.1	17.88	850
% Age 55 and Older	27.81	3.24	14.14	37.22	850

Estimates weighted by annual state population.

Income, Medicaid, and Medicare are in real 2000 U.S. dollars.

insurance mandate is positive for both specifications. Columns (3) includes the estimates including state and year fixed effects. The exponentiated coefficient suggests that states which enact SAT mandates have admission incidence rates 13 percent higher than in states where there is no law in effect and is significant at the 95 percent level of confidence. Column (4) includes the estimate when including state-specific time trends along with fixed effects. The magnitude on the coefficient is higher than under the fixed effects specification at 0.23 but is not statistically different than the fixed effects coefficient at conventional significance levels. Due to the heterogeneity in SAT rates from state-to-state in both average and trends, Columns (4) is the preferred specification.

The primary conclusion is that states which enact laws mandating insurance coverage for SAT see substantial increases in treatment. This is indicative that the affected population (employed and capable of maintaining health insurance coverage) has an unmet demand for SAT in absence of legislation. However, this analysis does not reflect the severity of conditions being treated or give any indication of whether individuals are on the margin of receiving treatment. In a later section, I explore this by repeating this analysis for admissions across drug concern, source of referral, and setting for admission.

Overdose Deaths

In this section, I report and detail the empirical findings on the impact of SAT insurance mandates on overdose death incidence rates as shown in Table 4.

Columns (1) through (4) reflect identical specifications as Table 3. Column (1) reports a significant positive estimate on the dummy variable for SAT insurance mandate; however, this is capturing a substantial amount of the overall upward trend in the OD rate which would be controlled for using time fixed effects and state-specific trends. Column (2) shows a small and insignificant decrease in accidental OD rate of about 7 percent

TABLE 3. Substance Abuse Laws and Admissions into Treatment

	Dep. Var.: log SAT rate			
	(1)	(2)	(3)	(4)
SAT Insurance Law	0.28	0.18	0.13**	0.23**
	(0.19)	(0.11)	(0.06)	(0.10)
Unemployment Rate		0.06**	-0.02	0.03
		(0.03)	(0.04)	(0.03)
Real Income per Capita		0.06***	-0.02	-0.01
		(0.02)	(0.02)	(0.02)
Medicaid per Capita		0.36***	0.14	-0.12
		(0.07)	(0.12)	(0.13)
Medicare per Capita		-0.54***	-0.83***	-0.77**
		(0.20)	(0.26)	(0.34)
% Female		-6.29	-0.94	82.21**
		(12.98)	(25.04)	(32.76)
% White (Non-Hispanic)		0.02***	0.06**	-0.04
		(0.01)	(0.03)	(0.09)
% Black		0.01	0.02	-0.34**
		(0.01)	(0.06)	(0.14)
% Age 15-24		-0.07	-0.09	-0.36*
		(0.10)	(0.09)	(0.18)
% Age 25-34		-0.07	-0.07	-0.17
		(0.09)	(0.11)	(0.13)
% Age 35-44		0.00	-0.1	-0.17
		(0.10)	(0.12)	(0.17)
% Age 45-54		-0.15	0.1	-0.06
		(0.10)	(0.10)	(0.14)
% Age 55+		0.03	-0.02	-0.2
		(0.08)	(0.10)	(0.20)
Observations	822	822	822	822
Adjusted R2	0.04	0.50	0.85	0.88
Mean(Dep)	6.29	6.29	6.29	6.29
Controls		X	X	X
State and Year FE			X	X
State Time Trends				X

Notes:

Standard errors clustered at the state level are shown in parentheses.

Estimates are weighted by annual state population.

* $p < 0.10$ ** $p < 0.05$ ** $p < 0.01$

when controlling only for state economic conditions and demographics, suggesting that the effects are not robust to the inclusion of additional controls. Columns (3) and (4) provide fixed effects estimates and are both estimate the impact to be about a 11 percent decrease (again insignificant at conventional levels).[25]

The results suggest that states which enact laws see increases in treatment but that it is insufficient to significantly affect overdose. However, the consistently negative estimate may be suggestive that there is an empirical specification issue that is adding noise to the impact. In a later section, I include specifications in a robustness exercise which include a possible omitted variable of laws which affect treatment for other mental health conditions. These laws are often passed separately from SAT insurance mandates but can encourage treatment through referrals by mental health providers and a general increase in individuals concern for their health.

Heterogeneous Impacts on SAT

We should expect there to be be substantial heterogeneity in the treatment effect; for instance, treatment for alcoholism can be substantially different than for opiates; likewise treatment in an intensive inpatient setting is going to be substantially different than treatment in an ambulatory outpatient therapy program. Depending on the needs of the affected population, the enactment of SAT insurance mandates may affect admissions heterogeneously.

I report the analysis of the impact of SAT insurance mandates on admissions by drug reported as the primary concern, source of referral into treatment, and setting for admission in Tables 5 to 9. Specifications in odd numbered columns are equivalent to Column (3) of Table 3 and even numbers are analogous to Column (4).

[25]The p-value of Column (4) is 0.154.

TABLE 4. Substance Abuse Laws and Accidental Drug Overdose Deaths

	Dep. Var.: log OD rate			
	(1)	(2)	(3)	(4)
SAT Insurance Law	0.37**	-0.07	-0.11	-0.11
	(0.15)	(0.10)	(0.10)	(0.07)
Unemployment Rate		0.12***	0.06	0.06**
		(0.03)	(0.06)	(0.03)
Real Income per Capita		-0.01	-0.03	0.02
		(0.02)	(0.04)	(0.03)
Medicaid per Capita		0.14	-0.27	0.02
		(0.10)	(0.20)	(0.14)
Medicare per Capita		0.2	-0.22	-0.05
		(0.20)	(0.27)	(0.19)
% Female		-47.41**	-131.09***	-179.58***
		(20.71)	(38.20)	(35.00)
% White (Non-Hispanic)		-0.01**	-0.04	0.02
		(0.01)	(0.04)	(0.09)
% Black		0	0.11	0.30*
		(0.01)	(0.09)	(0.17)
% Age 15-24		-0.56***	-0.43***	-0.34**
		(0.11)	(0.13)	(0.13)
% Age 25-34		-0.32***	-0.38**	-0.44***
		(0.12)	(0.14)	(0.12)
% Age 35-44		-0.54***	-0.19	-0.32**
		(0.10)	(0.16)	(0.15)
% Age 45-54		-0.02	0.26**	0.37**
		(0.10)	(0.12)	(0.16)
% Age 55+		-0.22***	0.14	0.34**
		(0.07)	(0.09)	(0.16)
Observations	850	850	850	850
Adjusted R2	0.04	0.62	0.89	0.94
Mean(Dep)	1.44	1.44	1.44	1.44
Controls		X	X	X
State and Year FE			X	X
State Time Trends				X

Notes:

Standard errors clustered at the state level are shown in parentheses.

Estimates are weighted by annual state population.

* $p < 0.10$ ** $p < 0.05$ ** $p < 0.01$

By Primary Drug Concern

Admission rates for alcohol treatment are significantly higher in states which enact SAT insurance mandates. States which enact laws see 16 to 20 percent more alcoholism treatment admissions than no-law states. Likewise, admissions reporting marijuana increased by 20 to 29 percent while amphetamines[26] increased about 25 to 38 percent after a law is enacted. The effect on admission rates for tranquilizers[27] is not robust to the inclusion of state time trends, though the estimated coefficient is similar in magnitude (See Column (14)). Lastly, there was an increase in SAT for "other drugs," which includes over-the-counter-substances and inhalants, following the enactment of the law (when accounting for state trends). Overall, the laws are primarily driving increases in commonly treated substance abuse disorders, but not having a strong effect on addictions that are the driving force behind the rise in drug related mortality.

In contrast, there is no evidence that state laws have a significant impact on rates of admission reporting cocaine, opiates, or hallucinogens. The estimated coefficients are both small and insignificant at conventional levels. The lack of impact on opiates SAT admissions, in particular, is consistent with insignificant findings regarding the accidental OD rate. Deaths due to alcohol poisoning are not included in the OD rate and there are no recorded deaths where cannabis was the only contributing substance,[28] so the significant impact on treatments for abuse of these substances would not be expected to have a direct spillover impact on drug related mortality.

[26] Primarily methamphetamine (meth), but also includes other amphetamines such as MDMA and phenmetrazine as well as other stimulants such as methylphenidate.

[27] In this case, "tranquilizers" are actually an aggregate of benzodiazepines and non-benzodiazepine tranquilizers as well as barbiturates and non-barbiturate sedatives and hypnotics.

[28] A very small number of ODs have poisoning due to cannabis derivatives as a multiple cause of death (code T40.7).

TABLE 5. Impact of Laws on SAT by Primary Concern at Admission

	Dependent Variable: log admission rate reporting substance			
	(1)	(2)	(3)	(4)
	Alcohol	Alcohol	Cocaine	Cocaine
SAT Insurance Law	0.16**	0.20**	0.04	0.17
	(0.07)	(0.10)	(0.07)	(0.11)
Observations	822	822	822	822
Adjusted R2	0.9	0.92	0.8	0.87
Mean(Dep)	5.41	5.41	4.34	4.34
	(5)	(6)	(7)	(8)
	Marijuana	Marijuana	Opiates	Opiates
SAT Insurance Law	0.20***	0.29**	0.03	0.11
	(0.07)	(0.12)	(0.10)	(0.11)
Observations	822	822	822	822
Adjusted R2	0.82	0.88	0.93	0.95
Mean(Dep)	4.25	4.25	4.01	4.01
	(9)	(10)	(11)	(12)
	Hallucinogens	Hallucinogens	Amphetamines	Amphetamines
SAT Insurance Law	0.2	0.08	0.25**	0.38**
	(0.13)	(0.16)	(0.12)	(0.15)
Observations	812	812	822	822
Adjusted R2	0.76	0.83	0.94	0.96
Mean(Dep)	0.32	0.32	2.28	2.28
	(13)	(14)	(15)	(16)
	Tranquilizers	Tranquilizers	Other Drugs	Other Drugs
SAT Insurance Law	0.28***	0.22	0.01	0.31**
	(0.08)	(0.14)	(0.15)	(0.12)
Observations	822	822	822	822
Adjusted R2	0.82	0.87	0.57	0.67
Mean(Dep)	1.11	1.11	0.83	0.83
Controls	X	X	X	X
State and Year FE	X	X	X	X
State Time Trends		X		X

Standard errors clustered at the state level are shown in parentheses

Estimates weighted by annual state population

** $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$*

By Referral Source

Treatment effects are likely to be heterogeneous by admission referral source. In Table 6, I investigate the impact of implementation of SAT insurance mandates on admissions into treatment programs by referral source. "Self" admissions reflect all admissions that are made on behalf of the addict themselves. Admissions under the category "Care" include all admissions coming from other SAT programs, mental health practitioners, and all other medically licensed professionals. "Community" referrals include all admissions from schools, employers, defense attorneys, welfare assistance, and self-help groups like Alcoholics/Narcotics Anonymous. Treatment admissions from "Criminal Justice" referrals include those from any judge, probation officer, prosecutor, or any other person affiliated with the judicial system.

TABLE 6. Impact of Laws on SAT by Source of Referral at Admission

	Dep. Var.: log admissions by referral source			
	(1)	(2)	(3)	(4)
	Self	Self	Care	Care
SAT Insurance Law	0.1	0.21**	0.15	0.28**
	(0.07)	(0.09)	(0.10)	(0.13)
Observations	819	819	819	819
Adjusted R2	0.83	0.88	0.83	0.87
Mean(Dep)	5.13	5.13	4.35	4.35
	(5)	(6)	(7)	(8)
	Community	Community	Crim. Just.	Crim. Just.
SAT Insurance Law	0.16**	0.18**	0.07	0.25*
	(0.08)	(0.09)	(0.11)	(0.14)
Observations	818	818	818	818
Adjusted R2	0.79	0.87	0.72	0.83
Mean(Dep)	4.01	4.01	5.18	5.18
Controls	X	X	X	X
State and Year FE	X	X	X	X
State Time Trends		X		X

Standard errors clustered at the state level are shown in parentheses
Estimates weighted by annual state population
* p < 0.10 ** p < 0.05 *** p <0.01

In this case, there is an observable difference across specifications including state-specific time trends rather than fixed-effects alone for many referral sources. Excluding these trends, there is only a significant increase in admissions coming from community referrals of about 16 percent. When accounting for time trends, there is an increase in admissions across all categories of referral sources ranging from 19 to 25 percent.

I further break down admissions by referral setting across primary substance reported in Tables 7 and 8. Column specifications are analogous to Column (4) of Table 3. Self, substance abuse care, and criminal justice system referral admission rates were significantly higher for alcohol, marijuana, amphetamines, and tranquilizers. Referral rates from other community sources were significantly higher for marijuana conditions. There is also evidence that treatments from schools reporting methamphetamine significantly increased following passage of the law. Lastly, additional referrals for other drug conditions were primarily from employers and the criminal justice system. As expected, there is no evidence of significant increases for admissions into treatment for cocaine, opiates, or hallucinogens from any of the source of referral.

The significant effects across self admissions, other SAT referrals, community referrals, and court system referrals for alcohol, marijuana, and methamphetamine treatments suggest that more than just the marginal person demanding treatment are responding to these mandates. Individuals being referred to treatment from other SAT programs suggest that individuals are receiving treatment on the intensive margin because institutions recognize that individuals can now afford more treatment than previously. Lastly, the responsiveness of treatment coming from court system reveals that the insurance coverage is providing coverage for unexpected demand for services such as DUI/DWI and other mandated treatment.

TABLE 7. Impact of Laws on SAT by Referral and Drug Concerns - Part A

	Dep. Var: log admissions from column referral source						
	Self	SA Care	Other Care	School	Employer	Other Community	Crim. Just.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Alcohol			
SAT Insurance Law	0.19*	0.29**	-0.16	0.27	0.12	0.08	0.24*
	(0.10)	(0.12)	(0.19)	(0.27)	(0.17)	(0.13)	(0.13)
Observations	819	773	817	792	766	817	818
Adjusted R2	0.88	0.89	0.84	0.83	0.9	0.87	0.9
Mean(Dep)	4.16	2.69	2.7	0.33	0.64	2.79	4.35
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
				Marijuana			
SAT Insurance Law	0.26***	0.37**	-0.17	0.18	0.21	0.20**	0.29*
	(0.09)	(0.16)	(0.23)	(0.18)	(0.18)	(0.10)	(0.15)
Observations	818	770	815	782	756	809	818
Adjusted R2	0.86	0.88	0.84	0.85	0.83	0.86	0.85
Mean(Dep)	2.47	1.07	1.05	0.86	-0.16	1.77	3.57
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
				Cocaine			
SAT Insurance Law	0.12	0.13	-0.21	0.04	0.27	0.1	0.25
	(0.09)	(0.16)	(0.18)	(0.13)	(0.23)	(0.10)	(0.15)
Observations	818	762	809	653	707	808	817
Adjusted R2	0.86	0.9	0.83	0.61	0.88	0.85	0.81
Mean(Dep)	3.27	1.92	1.54	-2.16	-0.58	2.01	2.98
	(22)	(23)	(24)	(25)	(26)	(27)	(28)
				Opiates			
SAT Insurance Law	0.1	0.09	-0.2	-0.22	0.12	0	0.18
	(0.12)	(0.19)	(0.20)	(0.20)	(0.21)	(0.12)	(0.14)
Observations	818	770	814	559	662	801	815
Adjusted R2	0.95	0.92	0.87	0.71	0.83	0.91	0.91
Mean(Dep)	3.37	1.56	1.14	-2.62	-1.54	1.05	2.01

Notes:
Standard errors clustered at the state level are shown in parentheses.
All regressions include state and year fixed effects, state trends, and controls for economic conditions and demographics.
Estimates weighted by annual state population.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

By Admission Setting

Detoxification and rehabilitation services vary substantially on costs, location, and types of services provided. For example, many inpatient rehabilitation services include detoxification as well as therapy and provide health care assistance for individuals with

TABLE 8. Impact of Laws on SAT by Referral and Drug Concerns - Part B

	Self	SA Care	Other Care	School	Employer	Other Community	Crim. Just.
	Dep. Var: log admissions from column referral source						
	(29)	(30)	(31)	(32)	(33)	(34)	(35)
	Hallucinogens						
SAT Insurance Law	0.12	-0.28	-0.33	0.06	0.3	0.06	0.05
	(0.16)	(0.21)	(0.20)	(0.14)	(0.34)	(0.25)	(0.18)
Observations	770	578	653	354	182	625	775
Adjusted R2	0.74	0.77	0.66	0.71	0.74	0.74	0.83
Mean(Dep)	-1.11	-2.08	-2.37	-3.33	-3.97	-1.99	-0.58
	(36)	(37)	(38)	(39)	(40)	(41)	(42)
	Amphetamines						
SAT Insurance Law	0.23**	0.54***	-0.08	0.33*	0.34	-0.07	0.59**
	(0.11)	(0.16)	(0.20)	(0.17)	(0.22)	(0.11)	(0.23)
Observations	812	743	784	606	582	768	811
Adjusted R2	0.95	0.91	0.87	0.83	0.83	0.95	0.94
Mean(Dep)	0.98	-0.39	-0.51	-2.53	-2.46	-0.02	1.19
	(43)	(44)	(45)	(46)	(47)	(48)	(49)
	Tranquilizers						
SAT Insurance Law	0.22*	0.35*	-0.08	0.14	0.12	0.06	0.17
	(0.12)	(0.18)	(0.13)	(0.17)	(0.26)	(0.14)	(0.19)
Observations	802	689	794	386	438	715	796
Adjusted R2	0.86	0.86	0.81	0.52	0.72	0.77	0.8
Mean(Dep)	0.08	-1.22	-0.94	-3.59	-3.41	-1.37	-0.58
	(50)	(51)	(52)	(53)	(54)	(55)	(56)
	Other Drugs						
SAT Insurance Law	0.23	0.1	-0.26	-0.23	0.25*	0.41	0.35**
	(0.17)	(0.18)	(0.19)	(0.14)	(0.15)	(0.29)	(0.14)
Observations	811	654	771	598	343	710	802
Adjusted R2	0.67	0.74	0.72	0.64	0.61	0.6	0.54
Mean(Dep)	-0.39	-1.85	-1.63	-2.5	-3.82	-1.59	-0.51

Notes:
Standard errors clustered at the state level are shown in parentheses.
All regressions include state and year fixed effects, state trends, and controls for economic conditions and demographics.
Estimates weighted by annual state population.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

medical complications arising from withdrawal. Increasing insurance may be substantial enough to cover some levels of treatment but may not be sufficient to cover intensive and costly sessions. In contrast, increased insurance may allow people who previously would benefit from intensive therapy but settled for the cheaper less intensive options to switch.

Table 9 reports the estimates of this analysis investigating the heterogeneous impacts by admission setting. I find that states which enact laws have significantly higher rates of admission (between 19 and 32 percent) across all types of treatment when accounting for state-specific time trends. When considering fixed-effects only, I find that states which enact laws have about 19 percent more outpatient treatments than states which do not.

TABLE 9. Impact of Laws on SAT by Setting at Admission

	Dep. Var.: log SAT admission rate into a treatment setting							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inpatient	Inpatient	Outpatient	Outpatient	Rehab	Rehab	Detox	Detox
SAT Insurance Law	0.13	0.19**	0.19**	0.29*	0.09	0.22*	0.24	0.32*
	(0.12)	(0.09)	(0.08)	(0.16)	(0.07)	(0.12)	(0.17)	(0.19)
Observations	815	815	821	821	821	821	779	779
Adjusted R2	0.69	0.79	0.80	0.84	0.83	0.87	0.72	0.81
Mean(Dep)	5.18	5.18	5.80	5.80	6.03	6.03	4.54	4.54
Controls	X	X	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X

Notes:
Standard errors clustered at the state level are shown in parentheses.
Estimates weighted by annual state population.
"Inpatient" includes hospital and residential admissions
"Outpatient" includes ambulatory services
"Rehab" includes inpatient or outpatient rehabilitation treatments (may include detoxification)
"Detox" includes inpatient or outpatient detoxification treatments
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

I extend on this analysis in Tables 10 and 11 by investigating the impact for inpatient and outpatient treatment across reported substances. The results are consistent with previous analysis with the only observable impacts occurring for alcohol, marijuana, and amphetamines. The impact for outpatient treatment for marijuana is significant at the 95 percent level of confidence across both specifications and suggestions outpatient treatment was higher by 17 to 25 percent in states with laws. Similarly, outpatient treatment rates for amphetamines increased by 28 to 47 percent. For outpatient treatment of alcohol and tranquilizers, the fixed effects specification suggests a weakly significant coefficient of 0.14 and 0.22, respectively, but the significance disappears when controlling for trends. There is no evidence of an impact on outpatient treatment for cocaine, opiates, hallucinogens, or other drugs. Likewise, there is no indication of significant increases in inpatient treatment across any of the substances.

TABLE 10. Impact of Laws on Outpatient SAT by Drug Concern

	Dep. Var.: log outpatient admission rate by drug concern							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Alcohol	Alcohol	Marijuana	Marijuana	Cocaine	Cocaine	Opiates	Opiates
SAT Insurance Law	0.14*	0.21	0.17**	0.25**	0.03	0.14	0.01	0.15
	(0.07)	(0.12)	(0.07)	(0.12)	(0.08)	(0.12)	(0.11)	(0.16)
Observations	821	821	821	821	821	821	821	821
Adjusted R2	0.83	0.87	0.77	0.83	0.78	0.85	0.91	0.94
Mean(Dep)	4.98	4.98	4.13	4.13	3.92	3.92	3.55	3.55
Controls	X	X	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Amphetamines	Amphetamines	Tranquilizers	Tranquilizers	Hallucinogens	Hallucinogens	Other Drugs	Other Drugs
SAT Insurance Law	0.28*	0.47**	0.22**	0.21	0.12	0	-0.07	0.17
	(0.14)	(0.18)	(0.09)	(0.15)	(0.15)	(0.19)	(0.16)	(0.10)
Observations	820	820	821	821	805	805	818	818
Adjusted R2	0.92	0.95	0.73	0.8	0.75	0.82	0.53	0.65
Mean(Dep)	1.91	1.91	0.64	0.64	0.1	0.1	0.57	0.57
Controls	X	X	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X

Notes:
Standard errors clustered at the state level are shown in parentheses.
Estimates weighted by annual state population.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

TABLE 11. Impact of Laws on Inpatient SAT by Drug Concern

	Dependent Variable: log inpatient admission rate by drug concern							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Alcohol	Alcohol	Marijuana	Marijuana	Cocaine	Cocaine	Opiates	Opiates
SAT Insurance Law	0.1	0.14	0.07	0.18	0.02	0.12	0	0.12
	(0.12)	(0.10)	(0.12)	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)
Observations	813	813	813	813	811	811	814	814
Adjusted R2	0.84	0.89	0.79	0.85	0.68	0.78	0.87	0.91
Mean(Dep)	4.34	4.34	2.41	2.41	3.51	3.51	3.01	3.01
Controls	X	X	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Amphetamines	Amphetamines	Tranquilizers	Tranquilizers	Hallucinogens	Hallucinogens	Other Drugs	Other Drugs
Subs. Abuse in Law	0.16	0.12	0.19	0.14	0.17	-0.05	-0.12	0.2
	(0.12)	(0.11)	(0.13)	(0.14)	(0.13)	(0.17)	(0.23)	(0.20)
Observations	805	805	797	797	769	769	788	788
Adjusted R2	0.93	0.94	0.81	0.88	0.75	0.81	0.61	0.7
Mean(Dep)	1.01	1.01	0.17	0.17	-0.85	-0.85	-0.56	-0.56
Controls	X	X	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X

Standard errors clustered at the state level are shown in parentheses
Estimates weighted by annual state population
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Other Results

In this section, I explore the robustness of the results on SAT and OD rates to scope of laws and inclusion of mental health mandates. The results from this analysis can be found in Table 12. Columns (1a) and (2a) are identical to columns (3) and (4) of Table 3, respectively. Columns (1b) and (2b) are the same as columns (3) and (4) of Table 4. In Table 13, I also investigate sensitivity to enactment date as well definition of death rate.

<u>Definition of SAT Laws</u>

Substance abuse insurance mandates vary on two primary levels: whether the language in the law requires benefits to be included in all plans and the level of benefits that must be provided. In this section, I separate the laws into three categories.[29] The first, called "Parity" laws, are mandates which both require all plans to include or offer benefits in their plans for SAT and that these benefits must be "no more restrictive" than for physical health. The second category captures all other laws requiring benefits to be included or offered, but that these laws require some minimum level of benefits that differs from physical health (called "Minimum Mandated Benefits (MMB)"). The final category "Mandated if Offered (MIO)" include all laws which mandate a certain level of benefits but do not have requirements to include benefits in the plans. The results are included in columns (3a), (3b), (4a), and (4b).

States which enact Parity or MIO laws experience significant increases in SAT admission rates relative to having no law in effect (28 and 21 percent, respectively with trends). There is no evidence that MMB laws signficantly increase SAT rates. For accidental OD rates, there is no statistical evidence of an impact from substance abuse insurance laws when accounting for state trends. With state and year fixed effects, states

[29]These definitions are adopted from Lang (2013).

which enact parity laws experience a decrease in accidental OD rates of about 25 percent (significant at 95 percent confidence).

In addition to legislation affecting insurance benefits for the treatment of addiction, many states enacted legislation which directly increased benefits for mental illness treatment. In several cases, these mental health laws also increased benefits for SAT by defining addictive disorders as a type of mental illness or had a subsection which affected substance abuse conditions. Other states passed laws affecting mental illness excluding. These laws could also indirectly affect demand for SAT by treating co-morbid conditions which are correlated with substance abuse disorders. Additionally, mental health practitioners may refer people into SAT more frequently as the utilization of mental health services increases following the enactment of the mental health laws.

Columns (5a) and (6a) report the estimates of the impact of substance abuse insurance mandates on SAT and (5b) and (6b) for OD rates when controlling for "mental health only" (MH) laws. For SAT rates, I find that the inclusion of MH mandates do not significantly alter the estimated impact from substance abuse insurance. Likewise, there does not appear to be a significant impact on SAT rate from MH laws. The linear combination of these impacts (including their interaction) suggests that states which enact both laws see a 34 percent increase in SAT treatment admission rates (significant at the 99 percent level of confidence). However, this is not statistically different than having a substance abuse insurance law alone.

When accounting for mental health only laws, the impact from SAT insurance mandates on overdose death rates becomes significant at the 90 percent level of confidence. Moreover, the independent impact from MH laws are similar in magnitude. The linear combination of the coefficients and the interaction indicates that states which enact both laws are no better off in terms of impact on OD rates than states which enact one or the

TABLE 12. Robustness Checks: Scope of Law and Mental Health Laws

	Dep. Var.: log SAT admission rate					
Panel A:	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
SAT Insurance Law	0.13**	0.23**			0.15**	0.22*
	(0.06)	(0.10)			(0.07)	(0.12)
Parity for SAT			0.18**	0.28*		
			(0.07)	(0.16)		
MMB for SAT			-0.11	0.11		
			(0.11)	(0.09)		
Mand. if Offer. for SAT			0.22***	0.21**		
			(0.08)	(0.10)		
MH Insurance Law					0.04	0.15
					(0.10)	(0.11)
Observations	822	822	822	822	822	822
Adjusted R2	0.85	0.88	0.85	0.88	0.85	0.88
Mean(Dep)	6.29	6.29	6.29	6.29	6.29	6.29

	Dep. Var.: log OD rate					
Panel B:	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
SAT Insurance Law	-0.11	-0.11			-0.15	-0.16*
	(0.10)	(0.07)			(0.12)	(0.09)
Parity for SAT			-0.25**	-0.06		
			(0.11)	(0.07)		
MMB for SAT			0.17	-0.37		
			(0.13)	(0.24)		
Mand. if Offer. for SAT			0.10	0.22		
			(0.10)	(0.18)		
MH Insurance Law					-0.10	-0.15*
					(0.10)	(0.08)
Observations	850	850	850	850	850	850
Adjusted R2	0.89	0.94	0.90	0.94	0.89	0.94
Mean(Dep)	1.44	1.44	1.44	1.44	1.44	1.44

Controls	X	X	X	X	X	X
State and Year FE	X	X	X	X	X	X
State Time Trends		X		X		X

Notes:
Standard errors clustered at the state level are shown in parentheses.
Estimates weighted by annual state population.
"MH Insurance Law": explicitly excludes treatment for addictive disorders
** p < 0.10 ** p < 0.05 *** p <0.01*

other. This suggests that either type of mandate reduces accidental OD rates and that the commonalities in both types of laws (namely increasing benefits for treatment by professionals) may be the transmission method between legislation and reduced probability of death.

Placebo Tests

To check whether the impact of laws was simply an artifact of time incorrect specification of treatment, I perform an enactment date sensitivity analysis. Another concern is that the enactment of the insurance mandate is correlated with overall improvements to access to health care. To check for this, I regress the death rate due to acute digestive disorders on the insurance laws. Table 13 reports the results from this exercise.

To test sensitivity to enactment date, consider a "placebo" law enacted five years prior to the actual enactment date. In the table, the dummy variable identifying this law is labeled"Subs. Abuse Insurance Law Placebo." I regress log SAT admission and OD rates on this placebo law, controls, fixed effects, and state trends in Columns (1) and (2), respectively. I find no evidence that either SAT or OD rates significantly change due to this placebo law.

To test whether laws are representing overall improvements in health care, I regress the log of the number of deaths due to digestive system conditions, primarily hernias and appendicitis, on the enactment of the insurance law in Column (3). These conditions are common, acute, and treatable by medical intervention; if access to health care is generally increasing, we would anticipate that the number of deaths due to these conditions would decrease. I do not find evidence that deaths due to these conditions significantly changed following the enactment of the law.

TABLE 13. Robustness Checks: Placebo Tests

Dependent variable is log rate of:	SAT (1)	OD (2)	Dig. Sys. Death Rate (3)
Subs. Abuse Insurance Law			-0.01
			(0.01)
Subs. Abuse Insurance Law Placebo	0.01	-0.05	
	(0.04)	(0.04)	
	822	850	850
	0.88	0.94	0.95
	6.29	1.44	3.38

Notes:
Standard errors clustered at the state level are shown in parentheses.
Estimates weighted by annual state population.
"Digestive system death rate" includes deaths due to appendicitis, hernias, colitis, and other digestive system diseases.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Event Study

The estimates presented so far represent the causal effect of insurance mandates on outcomes, provided that the following holds: law makers are not responding to generally worsening conditions in substance abuse morbidity and mortality by enacting legislation to correct the issue. This potential source of endogeneity may cause positive bias in the effect of laws on SAT and negative bias in the effect of laws on overdose deaths.

To investigate whether this occurring, I implement an event study which creates a dummy variable for years before and after the passage of substance abuse laws. The year that the law becomes effective is coded as year zero and I create dummies for each year before and after this enactment year ($D^j_{st}, -5 \leq j \leq 5$). The dummy variable for $j = -5$ is one if the year is less than or equal to five years before enactment and the dummy variable for $j = 5$ is one if the year is more than or equal to five years after enactment. I regress log SAT admission rates and log OD rates on these dummies, state and year fixed effects, and a set of controls (omitted category is the enactment year where $j = 0$).

$$log(SA_{st}) = \beta_0 + \sum_{j=-5}^{5} (\beta_j D^j_{st}) + \Gamma X_{st} + \delta_s + \alpha_t + u_{st}$$

The coefficient β_j captures the log difference in the incidence rate of admissions or deaths j years after the enactment year relative to the year of enactment. In the case of admission rates, if there is a general decrease in β_j as time moves from $j = -5$ toward $j = 0$, then there is concern that policy makers may be responding to generally worsening conditions in substance abuse treatment by enacting the law. For accidental drug deaths, if β_j is increasing over this time, then law makers may be responding to heightened death rates by enacting the policy. If β_j is increasing (for SAT rates) or decreasing (for OD rates) prior to enactment, then it is difficult to determine if the coefficient is just picking up a trend in SAT and OD rather than the true causal effect.

This event study also permits us to examine the medium to long-run effect of these laws. For $j \geq 1$, the coefficient β_j reports how persistent the effect from the law has been. If the law is enacted and the effect continues, then these coefficients should be consistent and statistically different than zero. However, if an effect is temporary, then we could anticipate that the coefficients return toward zero.

Tables 14 report the estimates for the event studies for log admission and overdose rates, respectively. On the left hand side of each table, I report the estimate for β_j when $j \leq -1$ and on the right hand side I report the estimates for $j \geq 1$. There is no evidence that the log SAT rate prior to enactment is not statistically different than the year of enactment. However, the years prior to enactment had OD rates that were significantly higher than the year of enactment. Additionally, there was a downward trend prior to enactment of the law. This suggests that the interpretation of the impact of insurance mandates on OD rates should be taken with caution.

TABLE 14. Event Study for Enactment of Laws on SAT and OD Rates

	Years Prior To Enactment					Years Following Enactment				
	5+	4	3	2	1	1	2	3	4	5+
Panel A: SAT										
Log difference in rate from	-0.07	-0.11	-0.09	-0.03	0.01	0.06*	0.10*	0.15**	0.19*	0.06
year of enactment	(0.13)	(0.11)	(0.10)	(0.11)	(0.06)	(0.03)	(0.06)	(0.08)	(0.11)	(0.11)
	N = 822									
Panel B: OD										
Log difference in rate from	0.22	0.19	0.17*	0.14*	0.06	-0.02	0.05	0.02	0.07	0.11
year of enactment	(0.13)	(0.12)	(0.10)	(0.08)	(0.06)	(0.05)	(0.06)	(0.08)	(0.09)	(0.12)
	N = 850									

Notes:
Standard errors clustered at the state level are shown in parentheses.
Estimates weighted by annual state population.
Regression includes state and year fixed effects and controls for state demographics, economic conditions, and MH only laws.
$*\ p < 0.10 \quad **\ p < 0.05 \quad ***\ p < 0.01$

This table also indicates that the effect on SAT admissions was persistent and perhaps may have been slightly delayed, with the largest increases in admissions coming two or more years after the law was passed. After five years, the SAT treatment effect is no longer distinguishable from the year of enactment.

Conclusion

Over the last several decades, many states have been enacting health care reforms to increase coverage for substance abuse in insurance plans. The intent of these laws were to reduce dependency on addictive substances and increase overall social welfare. In this paper, I examine the impact of these policies on measures of effectiveness, namely substance abuse treatment (SAT) admissions and accidental overdose deaths (OD).

I find that the policies have a significant impact on SAT admission rates, but that there is substantial heterogeneity across admission types by drug reported as primary concern. In particular, laws increasing benefits for substance abuse treatment appear to primarily increase admissions for alcohol, marijuana, and amphetamines. Admissions for opiates, hallucinogens, and other drugs do not appear to change in response to mandates. New admissions are being referred into treatment from other SAT programs and the criminal justice system in addition to self-referrals, indicating an increase both on the intensive margin for treatment as well as for individuals not actively considering treatment. For marijuana treatment admissions, there are also additional treatments from other community referrals such as self-help groups and welfare assistance. Lastly, I find that there are significant increases to both inpatient and outpatient treatment.

I also investigate the impact of these laws on accidental OD rates. States which enact laws do not appear to have significant decreases in OD rates which is consistent with the findings for SAT where opiate and cocaine admissions did not appear to significantly change in response to legislation. When controlling for other mental health laws, there is a marginally significant decline in OD rates in states which enact a law. If this effect exists, it would be indicative that professional treatment, in general, is a mechanism for deterring overdose deaths.

I also find that the effect on treatment admissions took several years to reach highest impact. This is expected as it may take time for individuals to understand their benefits, allows old plans to expire and new plans to take place.

This paper adds to the existing literature on substance abuse, insurance markets, and health care policies in three ways. First, I precisely define the treatment through careful analysis of state legislation, identifying laws which directly address substance abuse; past literature focused on mental health laws which may or may not include substance abuse coverage. Secondly, I find that substance abuse insurance mandates are effective at increasing treatment, but that this is primarily for alcohol, marijuana, and amphetamines. Thirdly, I find evidence that laws are effective at increasing admissions from other SAT programs, the criminal justice system, and community groups which is indicative that the laws are increasing admissions for people who would not actively seek treatment on their own.

Future literature on this topic could include an in depth investigation on states which pass multiple substance abuse laws. Additionally, this paper indicates that mental health laws significantly decreased OD rates and future papers would further explore this result. Lastly, the these laws do not show a significant effect on opiate or cocaine treatment rates. Next steps would be to seek to identify whether other health care policies which affect other populations (such as Medicaid or Medicare) are effective at inducing individuals into treatment programs for these drug concerns.

In this chapter, I explore the impact of a large-scale public policy on substance abuse, a risky behavior that has become a wide spread health crisis in the United States. Another major concern in the United States has been high amounts of criminal activity, particularly during the early part of the 1990s. Many papers have drawn connections between poor economic conditions and criminal behavior. In my next chapter, I revisit this problem and question the assumptions made about the time-stability of this relationship.

CHAPTER III

THE EVOLVING CYCLICALITY OF ECONOMIC CONDITIONS AND CRIME

Introduction

Crime in the United States has been a consistent concern for policy makers and academics. In the early 1990s, crime reached a peak rate with nearly 5,500 property crimes and 500 violent crimes being reported per 100,000 population. This rate has declined steadily over time but continues to be high in some areas, particularly in urban and poorer regions. Understanding the determinants of the crime trends has been of continued interest to economists, and an influential literature on the specific effects of macroeconomic conditions has emerged.

Academic literature investigating the effect of economic conditions on crime have drawn the consistent conclusion that periods of high unemployment and low wages lead to increases in the property crime rate (Raphael and Winter-Ebmer (2001), Gould et al. (2002), Mocan and Rees (1999), Mocan and Bali (2010)). Each of these papers address some variation of the following empirical model, estimated using panel data at the state or county level.

$$\text{Crime Rate}_{st} = \beta_0 + \beta_1 \text{Unemployment Rate}_{st} + \varepsilon_s t$$

An assumption in this model is that the parameter β_1 is exogenous to external factors. However, there are reasons to suspect that this may not necessarily be the case. The parameter β_1 is understood to reflect the average person's choice to commit crimes in response to changes in unemployment.[1] In his seminal paper, Becker (2000) predicts that the choice to commit crime depends on the return to crime and the probability

[1] It may also capture changes in overall enforecement during periods of high unemployment.

of apprehension. In areas with high unemployment, the return to committing crime may be higher due to lack of legal sector income. At the same time, in areas with high unemployment the probability of apprehension may be higher due to more people spending time at home watching their valuables.

The literature has found little evidence that economic conditions are associated with violent crime. Indeed, the relationship is a priori ambiguous. Poor economic conditions may affect crime rates by changing the number and type of interactions people make on a daily basis. For example, increased unemployment may reduce a person's exposure to other individuals and therefore decrease their likelihood of committing a violent crime. Moreover, job loss reduces the amount of money that can be spent drinking at bars or attending sporting events where violent crimes are common (Madensen and Eck (2008); Scott and Dedel (2006)). Additionally, if unemployment is more severe for men than women, the relative wage gap between men and women decreases which corresponds to heightened bargaining power of females in the relationship and reduced domestic violence (Aizer (2010)). In contrast, increased joblessness heightens stress levels which can lead to increased propensity toward criminal acts (Linn et al. (1985); Agnew (1992); Eitle and Turner (2003)). Moreover, individuals are spending more time around family and experiencing financial stress, thereby increasing the number of opportunities for domestic violence to occur.

Over time, the probability of apprehension for property crimes has also increased as protection methods to secure valuables, such as tracking devices and home theft monitoring, has improved. This would lead to the typical person to be less likely to commit theft in response to the economic stresses of unemployment. Moreover, when economic conditions are poor, macroeconomic violent crime rates will depend on the traits of the unemployed and thus may be time variant.[2]

In this paper, I relax the assumption that the relationship between crime rates and economic conditions is constant across time. I utilize state panel data on arrests for crime in an ordinary least squares estimation model. In the first exercise, I take equal sized subsets of data over time and individual estimate the relationship between unemployment and crime rates. I find that this relationship for property crimes has diminished towards zero. Secondly, I allow for time heterogeneity in the parameter by interacting unemployment with a series of yearly dummy variables. Again, I find that for many property crimes the estimate appears to be falling throughout time and that the impact appears to mostly disappear by the most recent decade. I also find that the impact of unemployment on violent crimes is occasionally significant and non-zero for some periods in the sample.

I also explore heterogeneity in the impact of unemployment on crime rates across age groups. I find that those most affected by aggregate economic conditions are 25 to 44 years old. However, when allowing for parameters to vary over time, it becomes clear that all age groups are sensitive to unemployment at some period in time and that the relationship evolves over time.

This paper contributes to the small literature on the time-variance of the response of crime to business cycles. Gould et al. (2002) suggest that unemployment plays a lesser role in explaining crime over the last few decades and little to no part in the long-run change in crime. Instead, they find that wages are a better determinant for long-run changes in crime. Mocan and Bali (2010) examine whether there are asymmetric responses to crime

[2]For example, if the unemployed population is poorer on average, then unemployment may lead to substantially higher stress than if the unemployed population is less poor. Likewise, if the unemployed population is largely comprised of adult men, then we may expect fewer violent crimes on average.

across expansions and recessions by looking at how crime responds to unemployment when the labor market is worsening and when it is improving (one-year differences). They find that recovery times affect criminality significantly more compared to recessionary periods and that unemployment is positively related to crime across both recessions and expansions. Both of these papers, however, assume relationship between unemployment and crime is constant over time.

The remainder of this paper is structured as follows. I begin by describing the research design framework and describe the data used in this analysis. I then report my findings across various specifications, discuss heterogeneous trends in parameters, and conclude.

Empirical Methodology

I utilize a slightly modified version of the empirical model used by Mocan and Bali (2010).[3] The following estimating equation is the base specification.

$$C_{st} = \beta_0 + \beta_{1t} U_{st} + X_{st}\Omega + \delta_t + \alpha_s + \Gamma_{st} + u_{st} \tag{3.1}$$

Here, crime rates C in state s during year t are a function of the unemployment rate U, a vector of covariates X, and subject to state and year fixed effects (α and δ, respectively) as well as state-specific time trends in crime (Γ). The covariates included in X include demographic structure of the region (percent white, black, and Hispanic), age distribution, urbanization, alcohol consumption, and total inmates per capita. Each state also has a distinct mean level of crime and a unique change in mean crime across time which may be due to various factors such as law history, police budgets, and demographic trends.

[3] In this paper, their goal was to examine whether β_1 differs across expansions and recessions. Equation (1) is a generalized version of the empirical model they presented.

The inclusion of state and time fixed effects along with state-specific time trends and covariates will control for these movements in crime and allow $\hat{\beta}_{1t}$ to capture the marginal change in crime due to a percentage point increase in unemployment. The inclusion of the t subscript on the parameter allows for time-variance in this generalized empirical model.

To begin, I assume that $\beta_{1t} = \beta_1$ for all t (i.e. that unemployment has a time-invariant effect on crime) and examine how this effect changes over various subsamples of the data. Next, I allow for a basic level of time-variance by allowing β_{1t} to vary across decades through the inclusion of dummy variable interactions.

Estimated Confidence Interval Plots

One way to examine whether there has been changes in the way that unemployment affects crime is through the use of estimated confidence interval plots. To do this, I assume that the parameter is time-invariant ($\beta_{1t} = \beta_1 \ \forall t$) and then estimate Equation (3.1) over a selection of smaller, equally-sized subsamples of the data. I then take the set of parameter and standard error estimates and plot them across time.

For the purpose of this paper, I focus on subsamples of ten to fifteen year lengths. To illustrate, the selection of subsamples with a window size of fifteen years would have years 1981 to 1996 in the first sample, 1982 to 1997 in the second, and so on. This totals fifteen small subsamples spanning the entirety of the data set.

I then regress the following time-invariant version of Equation (3.1) for each subsample $i \in [1, \ldots, n]$.

$$C_{st} = \beta_0 + \beta_1 U_{st} + X_{st}\Omega + \delta_t + \alpha_s + \Gamma_{st} + u_{st} \tag{3.2}$$

I obtain a vector of parameter estimates ($\hat{\beta}_1^1, \hat{\beta}_1^2, \ldots, \hat{\beta}_1^n$, where n is the number of subsamples) and associated standard errors and I plot 95 percent confidence intervals across the time span. Evidence of a change in parameter can be seen through analysis of the overlap of the confidence intervals and whether the confidence intervals include the full-sample estimate or zero. However, this sort of analysis has inherent difficulties because it relies heavily on the selected window size. For small windows, the model suffers from low power due to sample size restriction. For larger subsamples, the estimates converge toward the average estimate for the full sample.[4] [5] In order to compensate for these possible limitations, I repeat this analysis using narrow (ten years) and wider (fifteen years) selections.

Time-Varying Parameters

The estimated confidence interval methodology assumes that the parameter is time-invariant but looks at small spans of time separately. Unfortunately, this loses the ability to utilize the full power of the entire sample. An alternative is to use the full sample and allow the parameter to be time-variant by interacting the unemployment rate with a dummy variable for the year of interest. That is, I estimate

$$C_{st} = \beta_0 + \beta_1 U_{st} + \sum_{y=1982}^{2010} (\beta_y D_y U_{st}) + X_{st}\Omega + \delta_t + \alpha_s + \Gamma_{st} + u_{st} \tag{3.3}$$

where D_y equals one if the year is equal to y and zero otherwise. The effect during the first year (1981) is going to be captured by β_1 and the deviance from this base year is β_y for $y \geq 1982$. Thus, the effect of unemployment on crime for years after 1981 is the linear combination

[4] This problem is a special case of the trade-off between variance (power) and bias resulting from selecting data window sizes. The issue has been often noted in empirical literature.

[5] Ideally, the optimal window size would only include a single year, but this is not feasible given data constraints.

$$\beta_1 + \beta_y$$

A significant estimate for any given β_y indicates that there is sufficient evidence that the parameter is different from that estimated in the 1981. A test of the null that the linear combination $\beta_1 + \beta_y$ is equal to zero determines if there is remains a significant effect in year y.

I expand this analysis to look at the heterogeneous effects of unemployment (currently decade level time variation) on crime across different age groups. That is, I regress the crime rate of each age group $j \in \{15-24, 25-34, 35-44, \geq 45\}$ in state s and year t on the same set of regressors found in Equation 3.3.[6]

By allowing dummy variables for each year, I can take advantage of the power of the full sample and allow time-variance in the parameter without imposing any rigid functional form on how it might be changing. If the parameter is changing in the same way as the average, the results will be similar as the estimated confidence interval plots. However, if there are certain years that demonstrate uniquely different trends, this methodology would be preferable because estimated confidence intervals will smooth over these outliers.

Data Description

Data Sources

I utilize crime data obtained through the Federal Bureau of Investigation's Uniform Crime Reporting System (UCR). The UCR Program collects data from 18,500 law enforcement agencies throughout the country on the number of offenses and arrests

[6]That is, crime rate $C_{st} = C^j_{st}$.

made across a broad range of crime categories. State-level annualized data is publicly available through the FBI website. More detailed data, including offenses by age, gender, and ethnicity at the county level, has been made available through the Inter-University Consortium for Political and Social Research's (ICPSR) National Archive of Criminal Justice Data (NACJD). Details on definitions of each of the crime variables as defined by the UCR Program and list of imputations and modifications made to the data are available upon request.

I utilize state unemployment rates as a proxy for aggregate economic conditions in any given year. This data is obtained through the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) database.

I control for alcohol consumption, demographic decomposition, urbanization, and prison inmate population.[7] Data on alcohol consumption was obtained from LaVallee and Yi (2011) who found estimates of statewide consumption of beer, wine, and spirits between 1977-2012. Prisoner population information was obtained through the National Prisoner Statistics program, made available by the ICPSR. Demographic information was obtained through the widely used Surveillance, Epidemiology, and End Results (SEER) database, which creates annual estimates of population by age, gender, race, and ethnicity. Annual data on the percent of population living in urban areas was obtained from the U.S. Census Bureau Decennial Census Data.[8]

[7]These are comparable to the controls used in Mocan and Bali (2010).

[8]I create annualized urbanization data using a single exponential smoothing algorithm on the decennial values.

Summary Statistics

In this paper, "crime rates" are defined as the number of arrests made per 100,000 population in the a given state. Property crimes include larceny,[9] motor vehicle theft, and burglary.[10] Violent crimes include murder,[11] forceful rape, aggravated assault,[12] and robbery.[13] Because robbery is very similar to larceny, I examine it separately and exclude it in my aggregate violent crime definition. Table 15 reports the summary statistics for this study. On average, there were 4,170 reported arrests per 100,000 population for property related crimes. Sixty-five percent of these property crimes are larcenies, twenty-four percent are due to burglaries, and the remaining are due to motor vehicle theft. Across the sample, there was an average of 379 violent crimes per 100,000 population (337 aggravated assaults, 35 rapes, and 7 homicides).

There has substantial changes in these rates across time. As shown in Figure 5, the violent crime rate increases between 1970 and 1990, with only a modest decline following the 1980 to 1981 recession. The violent crime rate declines steadily thereafter. Property crime rates, on the other hand, have been more volatile. Between 1970 to 1980, property crime tended to increase and peaked at around 5250 crimes per 100,000 population. Between 1980-1985, property crimes declined but then increased again to a secondary peak just over 5,000 crimes in 1990 after which they began a steady decline.

The unemployment rate is often considered a good proxy of economic conditions in a year. Unemployment declines during expansions (usually with a small lag), and rises

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[9] Theft of another person's assets or property which involves carrying away of personal property without permission of owner without intent to return property.

[10] Theft which involves physical entrance into a building illegally.

[11] Murder in this paper will include manslaughter charges as well.

[12] Assault with the intention of cause serious bodily injury.

[13] Larceny which includes force or intimidation.

TABLE 15. Summary Statistics: Unemployment and Crime

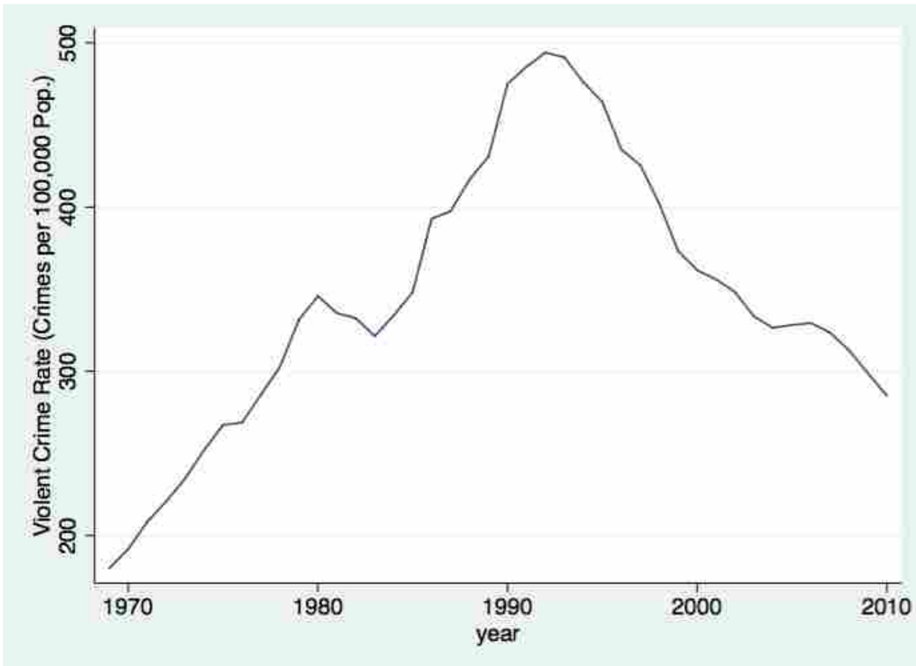
	Mean	SD	Min	Max	N
Property	4170.15	1209.05	1724.3	9512.1	1530
Larceny	2705.6	717.52	1273	5833.8	1530
MV Theft	469.22	226.23	70.1	1839.9	1530
Burglary	995.31	408.42	296.5	2727.3	1530
Robbery	189.35	116.2	6.4	1635.1	1530
Violent	378.85	155.63	40.6	1692.2	1530
Rape	34.85	11.4	7.3	102.2	1530
Agg. Assault	336.85	147.73	31.3	1557.6	1530
Murder	7.15	3.8	0.2	80.6	1530
Unemployment Rate	6.25	2.09	2.3	17.4	1530
% age 15-19	7.15	0.59	4.12	10.68	1530
% age 20-24	7.35	0.68	5.14	10.42	1530
% age 25-34	15.09	2.01	10.87	22.66	1530
% age 35-44	15.27	1.61	11.23	22.17	1530
% age 45-54	13.58	1.84	8.15	17.88	1530
% age < 15 or 55+	41.56	2.44	30.57	49.68	1530
% White (non-Hispanic)	71.95	14.21	21.62	98.58	1530
% Black	12.75	8.11	0.24	69.94	1530
% Native American	0.99	1.64	0.08	17.19	1530
% Asian Decent	3.81	5.65	0.31	72.84	1530
% Hispanic Origin	11.43	11.11	0.43	46.39	1530
% Urban	68.17	16.65	15.48	100	1530
Inmates per 100k pop	320.46	136.13	36.09	1651.79	1520
Beer (gal. per capita)	1.26	0.2	0.7	2.18	1530
Wint (gal. per capita)	0.34	0.15	0.08	1.11	1530
Spirits (gal. per capita)	0.73	0.22	0.36	2.92	1530

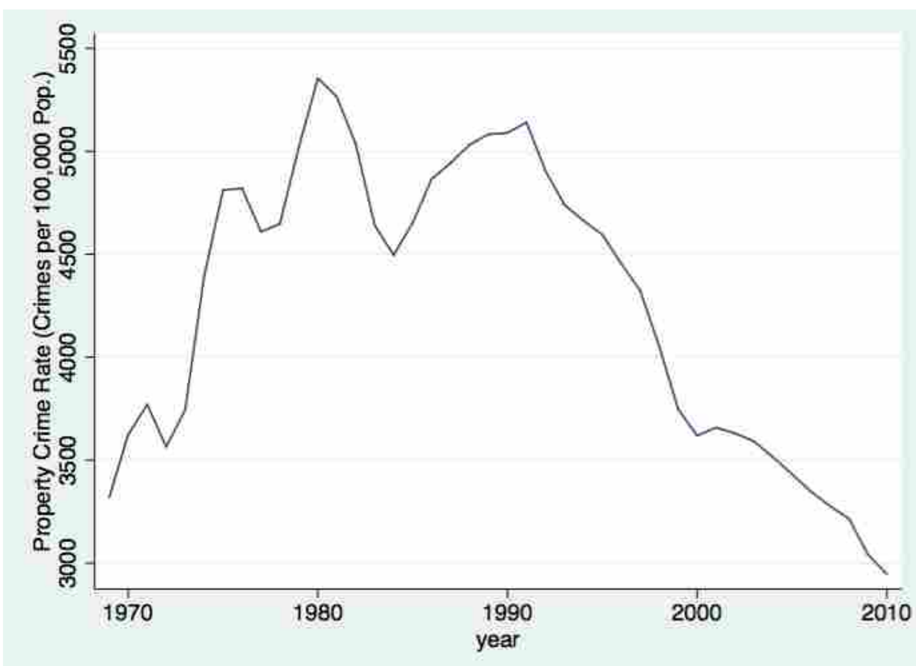
Estimates are weighted by annual state population.

during recessions. The average unemployment rate across this time span was about 6.25 percent. The largest peaks in unemployment follow the 1980-1981 recessions and the 2007-2007 Great Recession. Other covariates with crime were also included in this analysis. First, I included the age, race, and ethnicity composition. Across this time period, teens(15-19) and young adults (20-24) made up an average 14.5 percent of the population. Property crimes, in particular, may very well be sensitive to the number of young people in the population.[14] About 72 percent of the population was white/non-hispanic origin, 13 percent black, and 4.7 percent indicated they were of either American Indian/Alaskan

[14]Freeman (1999) and Mocan and Bali (2010) both find age to be a significant controlling factor in similar analysis.

FIGURE 5. Property and Violent Crime Rates in the United States (1960-2010)





Native or Asian/Pacific Islander decent. The large majority of the population was in urbanized areas (77 percent). Other covariates included in the analysis were for alcohol consumption and prison incarceration rates. The amount of alcohol consumed per capita[15] is about 1.3 gallons of beer, 0.3 gallons of wine, and 0.7 gallons of hard alcohol every year. The number of prison inmates comes from the National Prisoner Statistics survey. On average each state had about 321 inmates per 100,000 population.

Results

Base Specification

Tables 16 and 17 report the time-invariant results of Equation (3.1). Odd numbered columns include state and year fixed effects and even numbered columns add in state-specific trends. Similar to the previous literature, I find a strong positive relationship between unemployment and property crimes where a one percentage point increase in unemployment translates to an additional 94.2 to 112.8 property crimes per 100,000 population. Decomposing the effect across types of property crimes, we find this large number comes from mostly larcenies and burglaries (56.1 and 33.0 additional crimes per 100,000 population, respectively). Motor vehicle thefts see a small increase of about 12.0 additional arrests per 100,000 population, but this is not robust to the inclusion of state trends. Among violent crimes, only robberies respond to changes in unemployment. For a one percent increase in unemployment, there is an increase of 6.5 robberies per 100,000 population.

[15] For population aged 14 and older.

TABLE 16. Impact of Unemployment on Property Crime Rates

	Dep. Var.: arrests per 100,000 population for given crime							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Property	Property	Larceny	Larceny	MV Theft	MV Theft	Burglary	Burglary
Unemployment Rate	112.80***	94.23***	63.53***	56.12***	12.02**	5.18	37.27***	32.97***
	(21.75)	(22.81)	(14.42)	(16.82)	(4.88)	(4.31)	(7.44)	(4.62)
% Female	62770.34**	-3.4e+04	31625.12	-3.0e+04	5692.12	-2.2e+04**	25459.23***	17959.43*
	(30299.07)	(30815.21)	(19606.13)	(20383.61)	(11423.99)	(9492.56)	(7990.04)	(9410.56)
% Age 0-14	-2.35	-89.56	-18.70	-61.87	-6.73	-7.64	23.06	-20.14
	(92.29)	(64.74)	(55.02)	(38.78)	(25.75)	(26.37)	(31.11)	(19.09)
% Age 15-19	-87.16	-26.24	-21.86	26.09	-8.77	24.10	-56.60	-76.45**
	(105.86)	(70.32)	(89.09)	(49.63)	(34.19)	(34.51)	(36.09)	(32.48)
% Age 35-44	-100.72	-338.76***	-13.42	-169.39***	-101.07***	-94.28***	13.69	-75.18**
	(97.24)	(105.83)	(68.21)	(61.86)	(32.53)	(25.55)	(31.04)	(36.03)
% Age 45-54	-175.60	-347.52**	-41.55	-128.67	-100.45*	-77.39*	-33.60	-141.51***
	(154.54)	(166.76)	(80.74)	(104.49)	(54.72)	(40.14)	(47.99)	(36.07)
% Age 55+	-119.19	-209.13	-96.02	-82.59	2.02	-36.13	-25.28	-90.59**
	(123.16)	(162.51)	(77.80)	(88.59)	(32.84)	(47.91)	(38.33)	(44.49)
% White (non-hispanic)	223.50**	143.08	96.10	103.26*	76.31**	35.43	51.12*	4.43
	(98.92)	(107.35)	(57.83)	(52.01)	(31.21)	(53.65)	(30.02)	(30.81)
% Black	84.04	176.76*	9.81	131.26**	66.61**	50.38	7.63	-5.08
	(117.79)	(90.56)	(71.81)	(56.12)	(29.73)	(40.31)	(36.34)	(29.59)
% Hispanic	98.62	-265.74**	17.44	-170.74***	83.23**	-1.18	-2.05	-93.77**
	(146.02)	(120.69)	(88.86)	(53.48)	(40.79)	(73.73)	(42.73)	(42.96)
% Urban	10.94	-2.61	4.68	-1.72	8.89*	11.36*	-2.64	-12.20**
	(18.57)	(15.64)	(12.27)	(9.29)	(5.30)	(5.76)	(5.45)	(5.06)
Gal. Beer Per Capita	2554.76***	420.59	1588.02***	197.90	462.11**	184.93*	503.95**	37.03
	(766.65)	(512.46)	(414.23)	(317.81)	(205.62)	(104.32)	(238.72)	(159.75)
Gal. Wine Per Capita	54.00	1001.50	568.19	692.58	-581.24***	-6.27	66.53	314.31*
	(739.15)	(713.99)	(539.45)	(466.14)	(206.29)	(193.60)	(228.54)	(175.66)
Gal. Liquor Per Capita	712.33	-607.48	278.80	-159.02	190.26	-72.31	243.45	-375.98**
	(679.53)	(573.04)	(344.82)	(341.14)	(200.19)	(103.01)	(222.27)	(182.97)
Inmates Per 100k Pop.	-1.15	-2.13*	-0.39	-0.81	-0.18	-0.38*	-0.58*	-0.94**
	(1.08)	(1.25)	(0.53)	(0.72)	(0.31)	(0.22)	(0.34)	(0.36)
Observations	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.91	0.96	0.90	0.95	0.81	0.91	0.93	0.96
Mean(Dep)	4169.41	4169.41	2705.27	2705.27	468.62	468.62	995.50	995.50
State and Year FE	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X

Estimates are weighted by annual state population.
Standard errors in parentheses are clustered at the state level.
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Estimated Confidence Intervals

Figures 6 and 7 show the estimated confidence interval (ECI) plots for a window size of fifteen years. The red dashed line is the estimated average effect from Tables 16 and 17. For property crimes, there is a clear downward trend in the parameter estimate. For samples excluding the years 2000 and onward, the parameter estimate was significantly larger than the estimated parameter in the base model. For samples containing 1985 to

TABLE 17. Impact of Unemployment on Violent Crime Rates

	Dep. Var.: arrests per 100,000 population for given crime									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Robbery	Robbery	Violent	Violent	Rape	Rape	Assault	Assault	Murder	Murder
Unemployment Rate	10.52***	6.53***	-0.37	-0.13	0.03	-0.19	-0.33	0.19	-0.08	-0.13
	(2.12)	(1.46)	(3.01)	(3.32)	(0.21)	(0.24)	(2.93)	(3.19)	(0.10)	(0.09)
% Female	1476.59	-2869.15	-7697.67	-7086.33	330.40	937.33*	-8090.67	-8022.32*	62.60	-1.34
	(3434.21)	(1928.56)	(5721.98)	(4639.32)	(432.66)	(483.38)	(5725.66)	(4713.38)	(100.19)	(86.11)
% Age 0-14	27.18*	0.31	20.88*	6.81	-0.39	-2.25*	21.00*	9.37	0.28	-0.31
	(14.34)	(7.80)	(11.72)	(11.05)	(1.03)	(1.28)	(11.45)	(11.21)	(0.30)	(0.29)
% Age 15-19	-6.94	-8.25	-1.94	8.46	0.32	-0.71	-2.25	9.73	-0.02	-0.56
	(11.78)	(10.03)	(18.41)	(19.50)	(1.38)	(1.44)	(17.84)	(19.20)	(0.47)	(0.39)
% Age 35-44	-11.20	-29.03**	-31.87**	-38.22***	0.29	1.32	-30.92**	-38.93***	-1.24**	-0.60
	(12.05)	(13.57)	(14.38)	(13.04)	(1.38)	(1.59)	(13.71)	(12.97)	(0.52)	(0.42)
% Age 45-54	23.12	-19.65*	-25.94	-35.36*	0.47	-1.36	-26.52	-34.07*	0.11	0.07
	(22.70)	(10.33)	(19.35)	(19.76)	(1.42)	(1.56)	(18.84)	(19.71)	(0.58)	(0.48)
% Age 55+	34.66**	-13.97	15.17	-3.76	-0.68	-2.43	16.14	-1.05	-0.29	-0.28
	(15.45)	(11.14)	(15.44)	(13.25)	(1.40)	(1.46)	(14.73)	(13.21)	(0.51)	(0.45)
% White (non-hispanic)	32.49**	11.69	9.56	-41.89*	2.06**	0.82	7.19	-42.31*	0.31	-0.40
	(15.72)	(23.12)	(10.71)	(22.13)	(0.98)	(1.36)	(10.06)	(22.64)	(0.44)	(0.57)
% Black	30.07**	24.12	8.02	-12.06	0.42	0.18	7.33	-13.04	0.27	0.80*
	(14.57)	(17.97)	(11.54)	(18.44)	(1.06)	(1.35)	(10.77)	(18.52)	(0.45)	(0.46)
% Hispanic	43.94*	-5.62	7.32	-64.18***	1.09	-1.46	6.26	-62.45**	-0.03	-0.27
	(22.45)	(26.24)	(14.72)	(23.89)	(1.03)	(1.53)	(14.08)	(24.04)	(0.57)	(0.77)
% Urban	2.22	1.40	1.28	4.96	-0.12	0.31	1.28	4.57	0.11**	0.07
	(2.31)	(1.61)	(2.51)	(2.99)	(0.17)	(0.23)	(2.42)	(2.97)	(0.05)	(0.07)
Gal. Beer Per Capita	253.36**	99.51**	146.38*	201.96***	9.22	8.74	134.65*	191.94***	2.51	1.27
	(105.15)	(41.44)	(78.44)	(63.21)	(6.72)	(5.63)	(75.26)	(63.44)	(2.46)	(1.32)
Gal. Wine Per Capita	1.86	6.81	61.35	42.66	10.41	-8.38	54.62	50.47	-3.68	0.57
	(82.15)	(63.24)	(85.85)	(103.74)	(9.19)	(8.19)	(81.07)	(100.70)	(3.10)	(2.43)
Gal. Liquor Per Capita	271.81***	-21.08	113.15	-12.32	16.36**	4.22	95.26	-14.58	1.53	-1.96
	(100.69)	(47.97)	(109.48)	(78.95)	(6.24)	(5.03)	(102.93)	(78.24)	(4.80)	(3.14)
Inmates Per 100k Pop.	-0.00	-0.10	0.06	0.09	-0.01*	-0.00	0.07	0.09	-0.00	-0.00
	(0.11)	(0.07)	(0.11)	(0.10)	(0.01)	(0.01)	(0.11)	(0.09)	(0.01)	(0.01)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.88	0.95	0.91	0.95	0.87	0.92	0.90	0.95	0.86	0.91
Mean(Dep)	188.99	188.99	378.56	378.56	34.85	34.85	336.58	336.58	7.13	7.13
State and Year FE	X	X	X	X	X	X	X	X	X	X
State Time Trends		X		X		X		X		X

Estimates are weighted by annual state population.

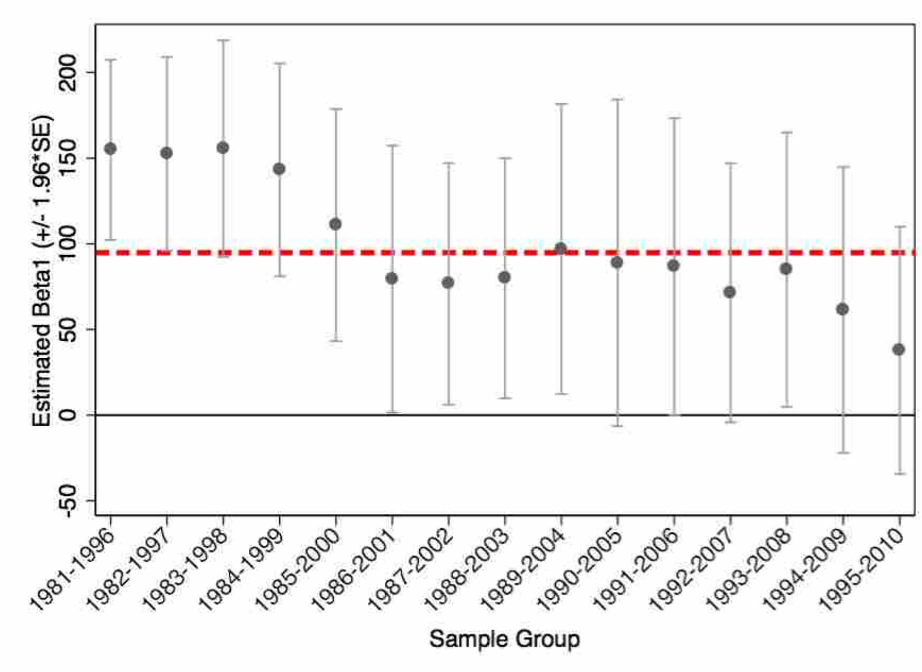
Standard errors in parentheses are clustered at the state level.

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

2007, there was no significant difference between the estimated coefficient of the sub-sample and the full sample. By the last 15 year window, however, the effect was not different than zero and significantly different than the full sample estimate at a 90 percent level of confidence. A similar exercise for violent crime rates show that the estimated impact hovered around zero and was not different than the full sample estimate.

For the smaller ten-year window size (Figures 8 and 9), the decrease across time for the property crime rates becomes much more pronounced. Furthermore, for windows containing only data post-1996, there is sufficient evidence to reject the null that the parameter is equal to the average one estimated by the full sample[16]. The estimates for violent crime are not distinguishable from zero (or the estimated average) across the span of sub-samples.

FIGURE 6. ECI Plot: Unemployment on Property Crime Rate (15 Year Window)



Time-Varying Parameters

From the previous analysis, I find evidence that the effect of unemployment on property crime appears to be diminishing over time regardless of window size selection. Moreover, hypothesis testing on the estimated parameters fails to reject zero for the majority of the most recent data. By shortening the window size, the downward trend becomes more apparent. This is suggestive that there is substantial yearly variation in the impact of unemployment and crime which cannot be picked up using estimated confidence

[16]Again, these results are consistent when weighted by mean crime rates.

FIGURE 7. ECI Plot: Unemployment on Violent Crime Rate (15 Year Window)

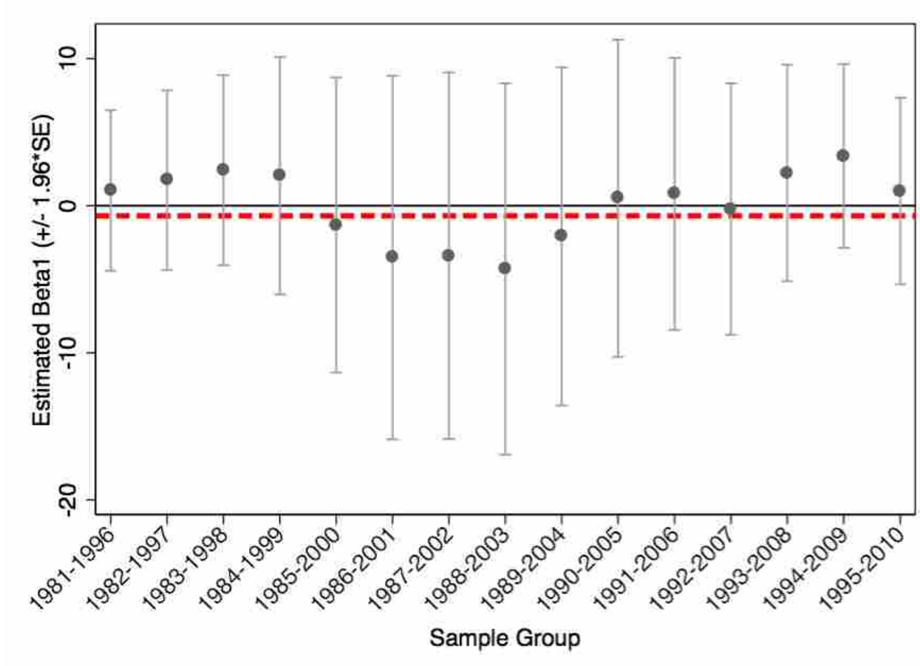


FIGURE 8. ECI Plot: Unemployment on Property Crime Rate (10 Year Window)

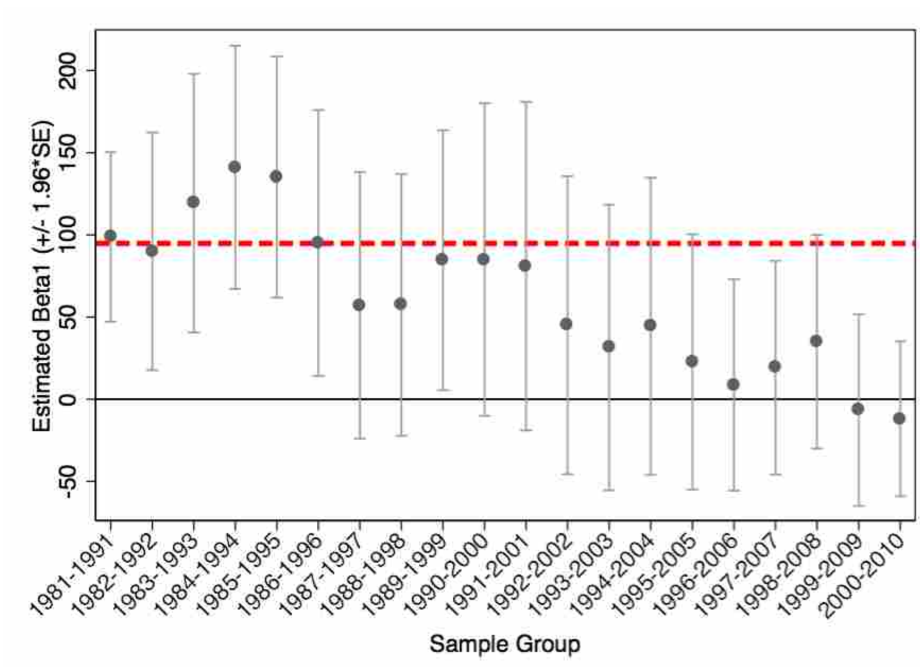
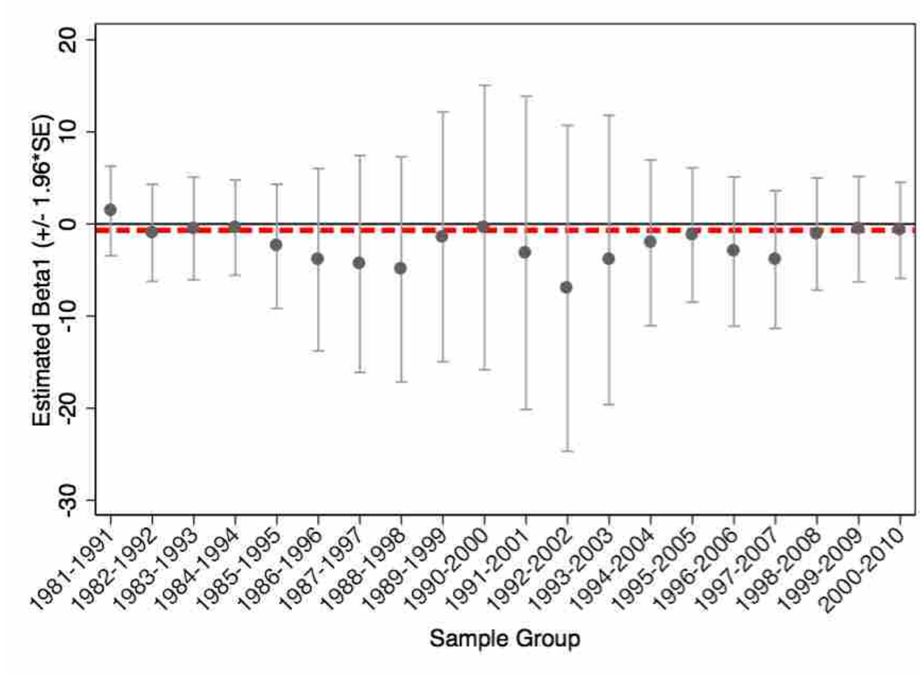


FIGURE 9. ECI Plot: Unemployment on Violent Crime Rate (10 Year Window)



interval plots. In this section, I report the results of the estimation where I allow the impact to vary annually by using dummy variable interactions with unemployment.

I plot the estimated effect of unemployment on crime between 1981-2010 in Tables 10a to 10i. The annual impact of unemployment on property crimes was significantly different than zero for years prior to 1996, after which the estimated impact fluctuates around zero. However, there is heterogeneity in the trends in parameter estimates for the component crimes. The parameter for larceny crimes declined until about 2000, rebounded temporarily during the next seven years. Arrest rates for motor vehicle thefts were positively correlated with unemployment until 1995, but then shifted to a negative correlation for the years after. The parameter on burglaries gradually diminished over the course of the sample with insignificant estimates in the years following 1996.

Robbery crime rates appear to have been positively related to unemployment and constant until 1996, after which the effect drastically declined and became insignificant.

FIGURE 10. Annual Impact of Unemployment on Crime Rates

The effect for other violent crimes was positive briefly during the early 1990s and then dropped below zero, though the effects are rarely significant. However, this trend can be attributed primarily to the effect coming from aggravated assaults. The estimate for rapes crimes appears to have a downward trend as well, with a significant negative impact by 2008. Lastly, the murder crime rate was unrelated to crime until the 1990s where the was a brief period when unemployment was positively correlated with murder. By the 2000s, murder was negatively correlated with unemployment.

Overall, there is evidence that the relationship between unemployment and crime is not static. A dramatic change occurs in 1996 for many property crime rates. Moreover, there is evidence that during some periods in time, unemployment has a non-zero relationship with violent crime rates.

Age Decomposition

In this section, I investigate heterogeneity in time-varying parameters for different age groups. More specifically, I estimate Equations 3.2 and 3.3 with crime rates for specific age groups or census divisions as the dependent variables. The purpose of decomposing by age group is two-fold. Firstly, it highlights whether age-specific crime rates are sensitive to macroeconomic changes in unemployment. Secondly, allowing time-varying parameters within age groups will indicate whether there are specific generations driving the results seen in the aggregate.

For this analysis, I construct the following age-specific crime rates:

$$R_{st}^{an} \ \frac{C_{st}^{an}}{P_{st}^{a}(100,000s)}$$

which is the number of arrests of persons from age group a for crime n in state s during year t per 100,000 population of age group a in state s during year t. I then estimate Equation 3.2 with the age-specific crime rates as the dependent variable. The results from this analysis are included in Table 18.

Columns (1) through (9) include regression estimates for the impact of macroeconomic unemployment on arrest rates of minors for property and violent crimes. None of the estimated coefficients are large in size or statistically significant at conventional levels. Columns (10) through (18) include the estimates for the impact of unemployment on arrests for crimes committed by young adults (18 to 24 years old). A

TABLE 18. Impact of Unemployment on Crime By Age Group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Ages 0-17				
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	12.89	8.11	1.05	3.73	1.70	2.76	0.01	1.07	-0.01
	(10.73)	(7.84)	(1.87)	(2.51)	(1.10)	(1.89)	(0.06)	(1.25)	(0.08)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.80	0.80	0.76	0.85	0.88	0.82	0.68	0.75	0.68
Mean(Dep)	687.70	473.64	66.95	147.11	45.94	119.31	5.88	70.77	2.60
					Ages 18-24				
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	24.12	13.99	1.35	8.79**	2.24	-0.00	-0.15	-1.05	-1.19
	(14.68)	(10.71)	(3.64)	(3.70)	(1.53)	(6.19)	(0.33)	(5.15)	(0.83)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.75	0.75	0.81	0.85	0.88	0.83	0.73	0.82	0.74
Mean(Dep)	1518.71	1032.71	143.10	342.90	156.65	524.60	26.50	345.61	22.35
					Ages 25-34				
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	19.92**	14.86**	0.77	4.29**	1.33	-2.70	-0.13	-3.52	-0.51
	(8.58)	(6.57)	(1.46)	(1.67)	(0.91)	(4.43)	(0.22)	(4.17)	(0.38)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.76	0.76	0.81	0.84	0.87	0.84	0.73	0.85	0.80
Mean(Dep)	769.80	563.91	58.12	147.78	66.71	331.94	18.05	254.24	10.99
					Ages 35-44				
	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	13.11**	10.88***	0.17	2.07*	0.49	-3.63	-0.04	-3.86	-0.26**
	(4.97)	(3.84)	(0.58)	(1.19)	(0.48)	(3.37)	(0.18)	(3.18)	(0.13)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.76	0.76	0.82	0.85	0.81	0.85	0.65	0.86	0.82
Mean(Dep)	471.70	369.99	27.57	74.13	27.88	195.63	10.85	161.95	5.81
					Ages 45-54				
	(37)	(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	1.42	1.34	-0.19	0.26	0.04	-1.57	-0.03	-1.46	-0.15***
	(1.79)	(1.60)	(0.21)	(0.39)	(0.16)	(1.40)	(0.08)	(1.34)	(0.05)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.81	0.80	0.82	0.91	0.82	0.87	0.58	0.87	0.80
Mean(Dep)	225.33	189.70	9.30	26.33	8.46	92.37	4.88	80.74	3.17
					Ages 55+				
	(46)	(47)	(48)	(49)	(50)	(51)	(52)	(53)	(54)
	Property	Larceny	MV Theft	Burglary	Robbery	Violent[a]	Rape	Assault	Murder
Unemployment Rate	0.04	0.14	-0.05	-0.05	-0.06	-0.30	0.01	-0.21	-0.03
	(0.80)	(0.74)	(0.06)	(0.11)	(0.04)	(0.24)	(0.02)	(0.24)	(0.02)
Observations	1520	1520	1520	1520	1520	1520	1520	1520	1520
Adjusted R2	0.82	0.83	0.73	0.83	0.67	0.85	0.57	0.85	0.80
Mean(Dep)	59.42	54.44	1.30	3.68	1.08	21.21	1.25	19.08	1.05

Estimates are weighted by annual state population.
Standard errors in parentheses are clustered at the state level.
All regressions include state and year fixed effects, state-specific time trends, and controls for demographics.
Violent[a] : non-robbery violent crimes (includes rape, aggravated assault and murder)
* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

one percent increase in the unemployment rate is associated with a higher level of burglary of about 8.8 arrests per 100,000 18-24 years olds. The impact on arrest rates for other crimes in this age group are insignificant at conventional levels.

The impact of unemployment on crime rates for adults aged 25 to 44 years can be found in Columns (19) to (36). Higher unemployment is associated with higher arrest rates for larceny and burglary for this group. For ages 25 to 34, arrests for larceny and burglary increased by 13.9 and 4.3 per 100,000 population, respectively, for a one percent increase in the unemployment rate. The estimated coefficients for 35-44 year olds were of similar magnitude at 10.9 and 2.1, though the average arrest rate in this age group was only about half of that for 25-34 year olds. Additionally, this age group experienced a significant decrease in murder rates during periods of higher unemployment of about -0.26 fewer murder arrests per 100,000 population.

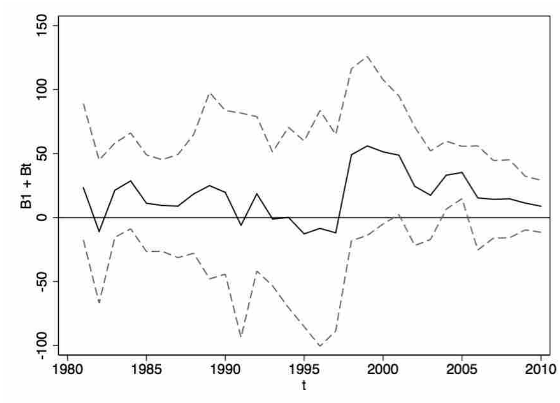
Lastly, the impact of unemployment on arrest rates for 45 and older ages are found in columns (37) to (54). The murder arrest rate for 45-54 year olds significantly decreased during periods of higher unemployment. Otherwise, there was no significant response to high unemployment for this age group.

I then allow parameter estimates to vary across time for each age group a and crime type n. I estimate Equation 3.3 and graph the linear combination of coefficients $\beta_{1981} + \beta_t$ for $t \in (1982, 2010)$ with a 95 percent confidence interval. These graphs can be found in Figures 11 to 19.

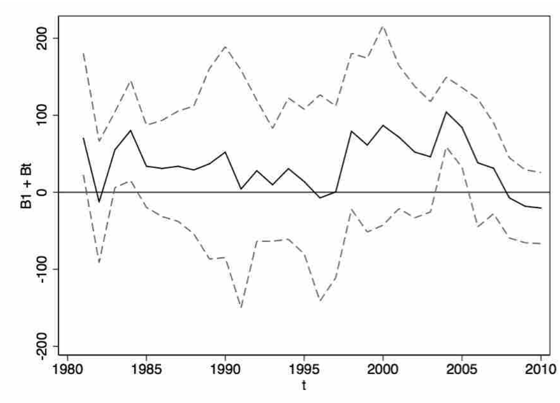
Arrests for larceny crime increased during periods of high unemployment for age groups 25 to 44 when the parameter was assumed to be constant. However, when allowing the parameter to change over time, there are a few noticeable differences. For all age groups, there was a significant increase in the parameter estimate in 1997 which eventually diminished over the next decade. The increase was less noticeable for ages 25-34 which

FIGURE 11. Annual Impact of Unemployment on Property Crimes By Age Group

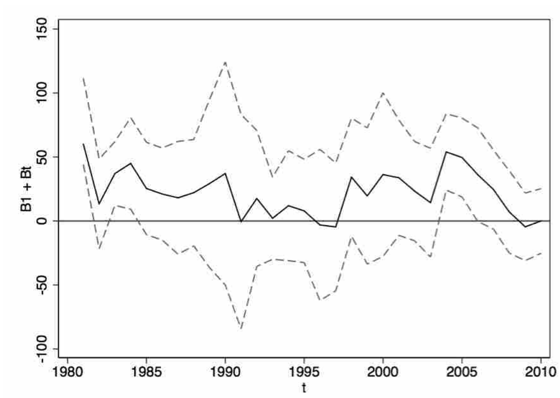
(a) Ages 0-17



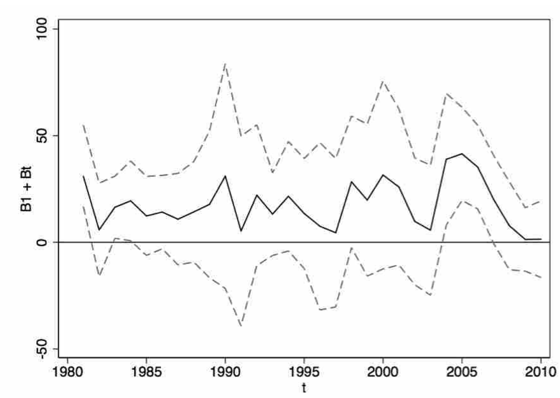
(b) Ages 18-24



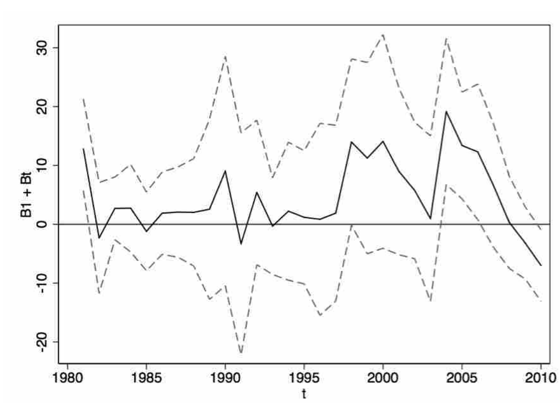
(c) Ages 25-34



(d) Ages 35-44



(e) Ages 45-54



(f) Ages 55+

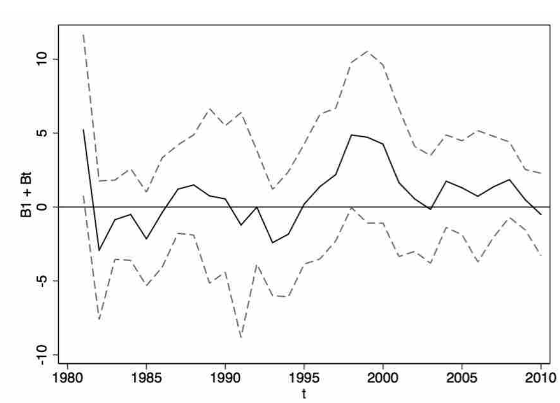


FIGURE 12. Annual Impact of Unemployment on Larceny By Age Group

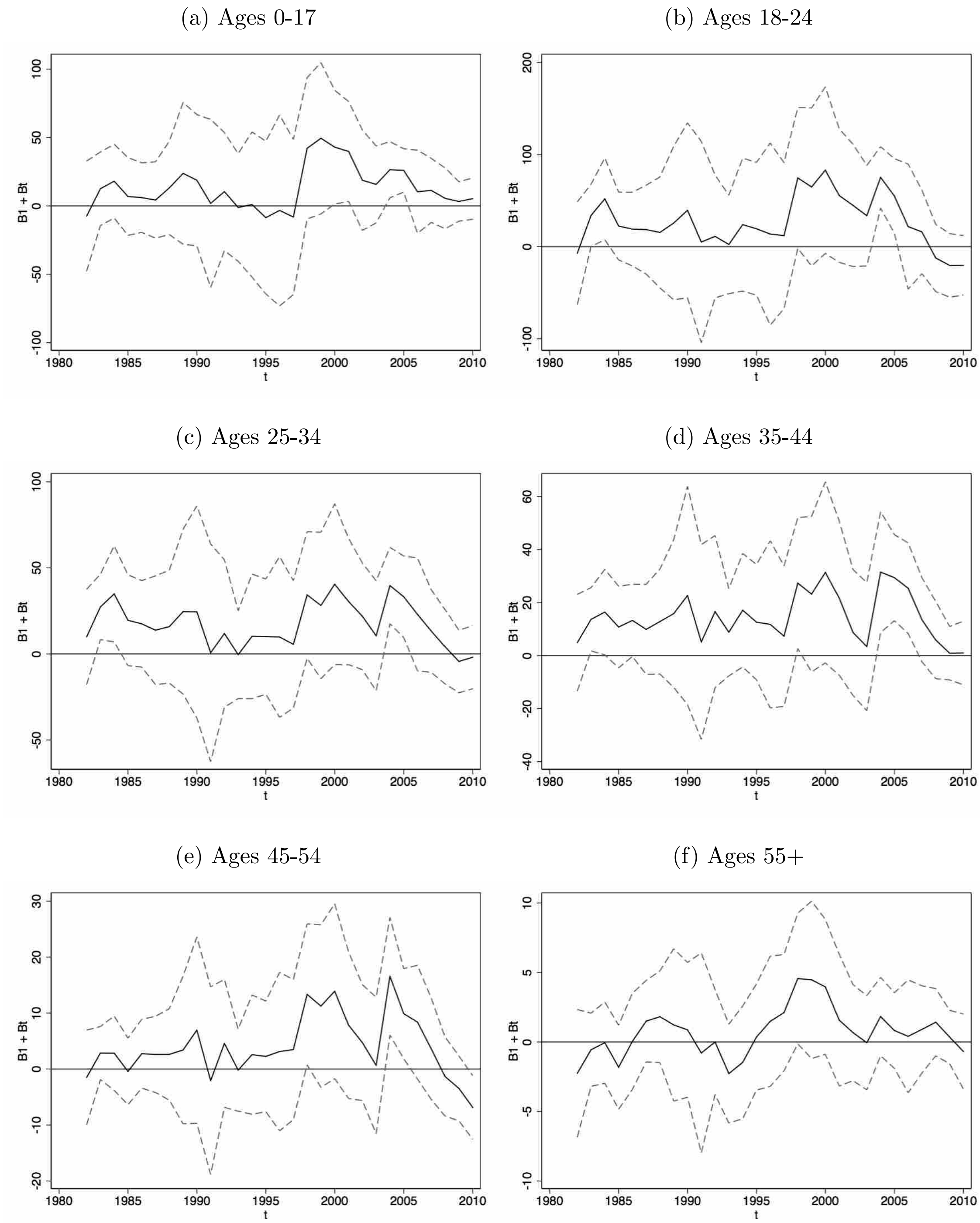
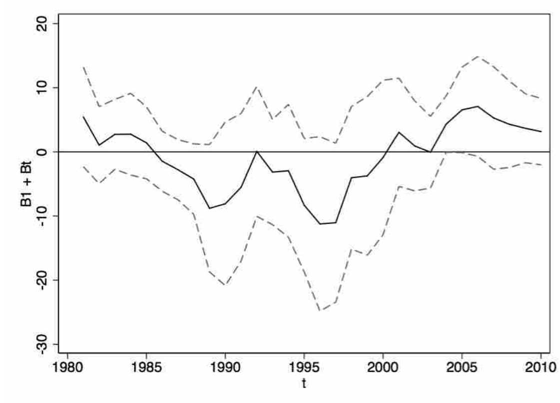
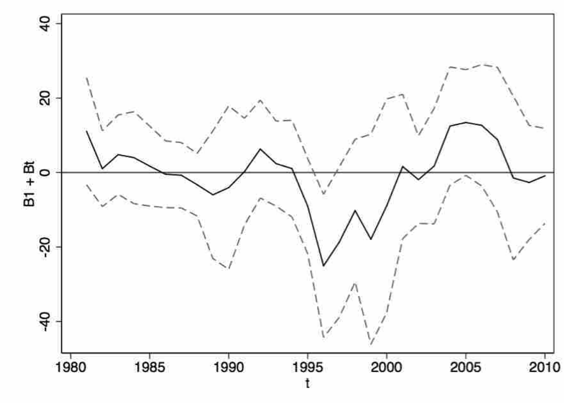


FIGURE 13. Annual Impact of Unemployment on MV Theft By Age Group

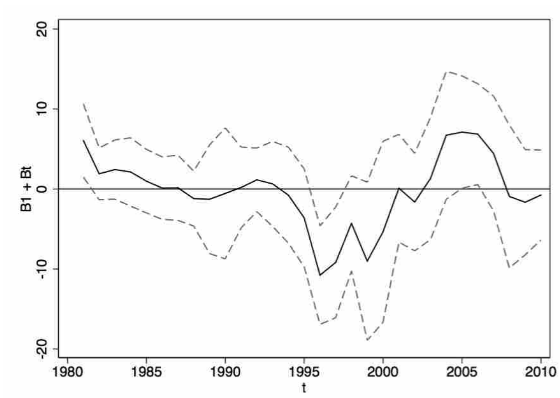
(a) Ages 0-17



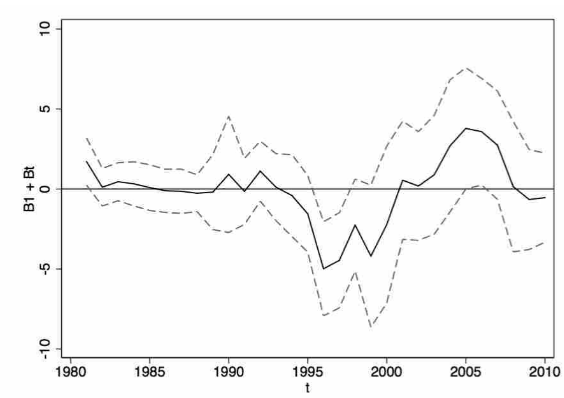
(b) Ages 18-24



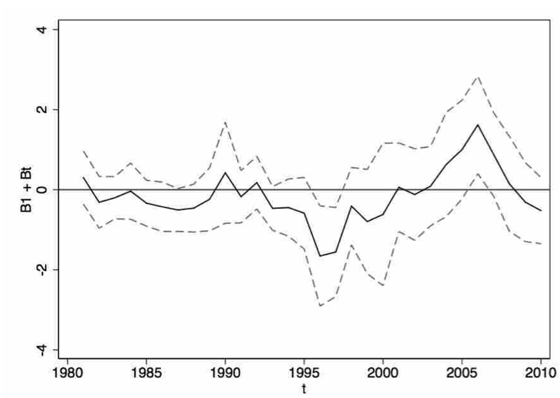
(c) Ages 25-34



(d) Ages 35-44



(e) Ages 45-54



(f) Ages 55+

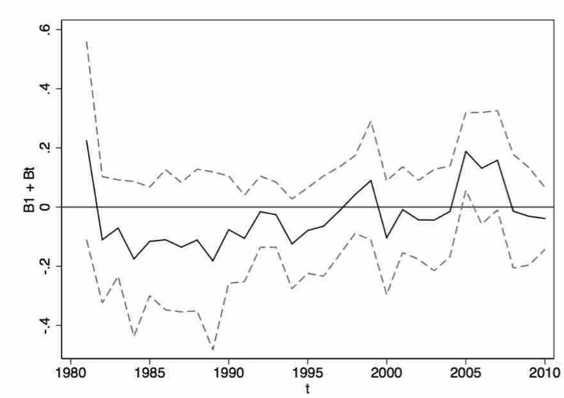
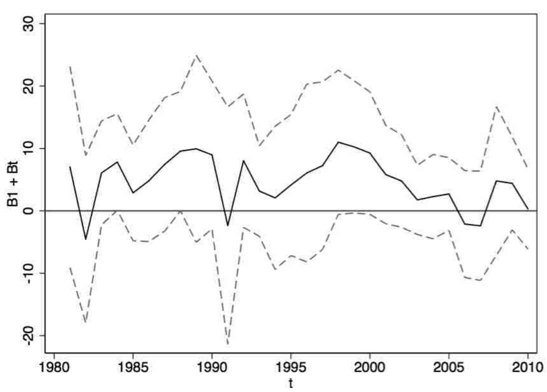
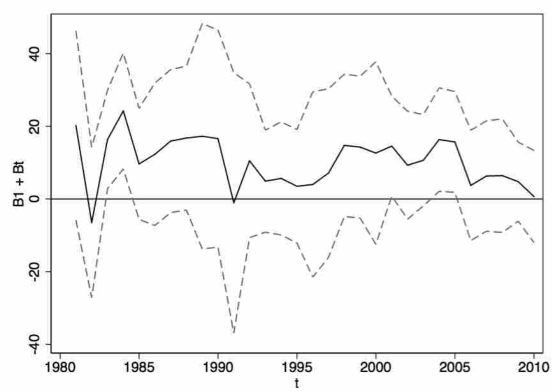


FIGURE 14. Annual Impact of Unemployment on Burglary By Age Group

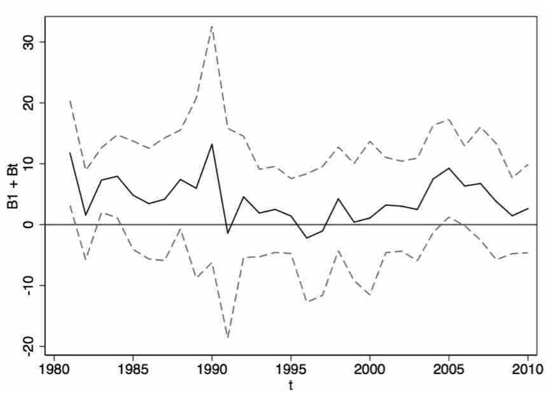
(a) Ages 0-17



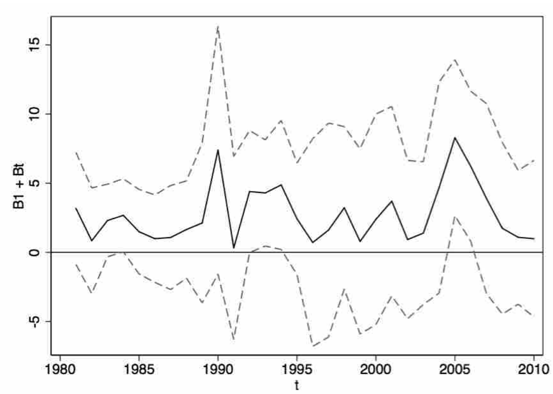
(b) Ages 18-24



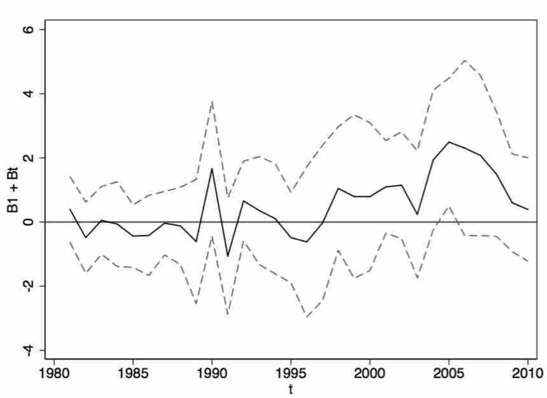
(c) Ages 25-34



(d) Ages 35-44



(e) Ages 45-54



(f) Ages 55+

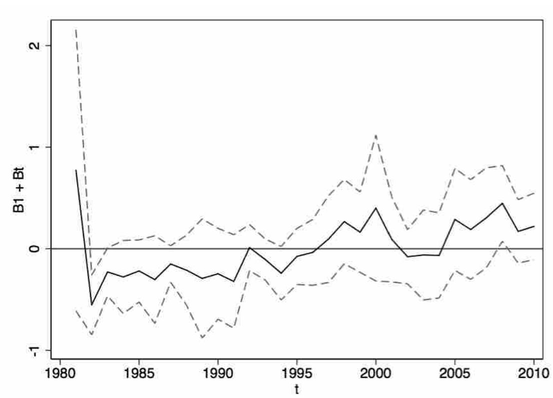
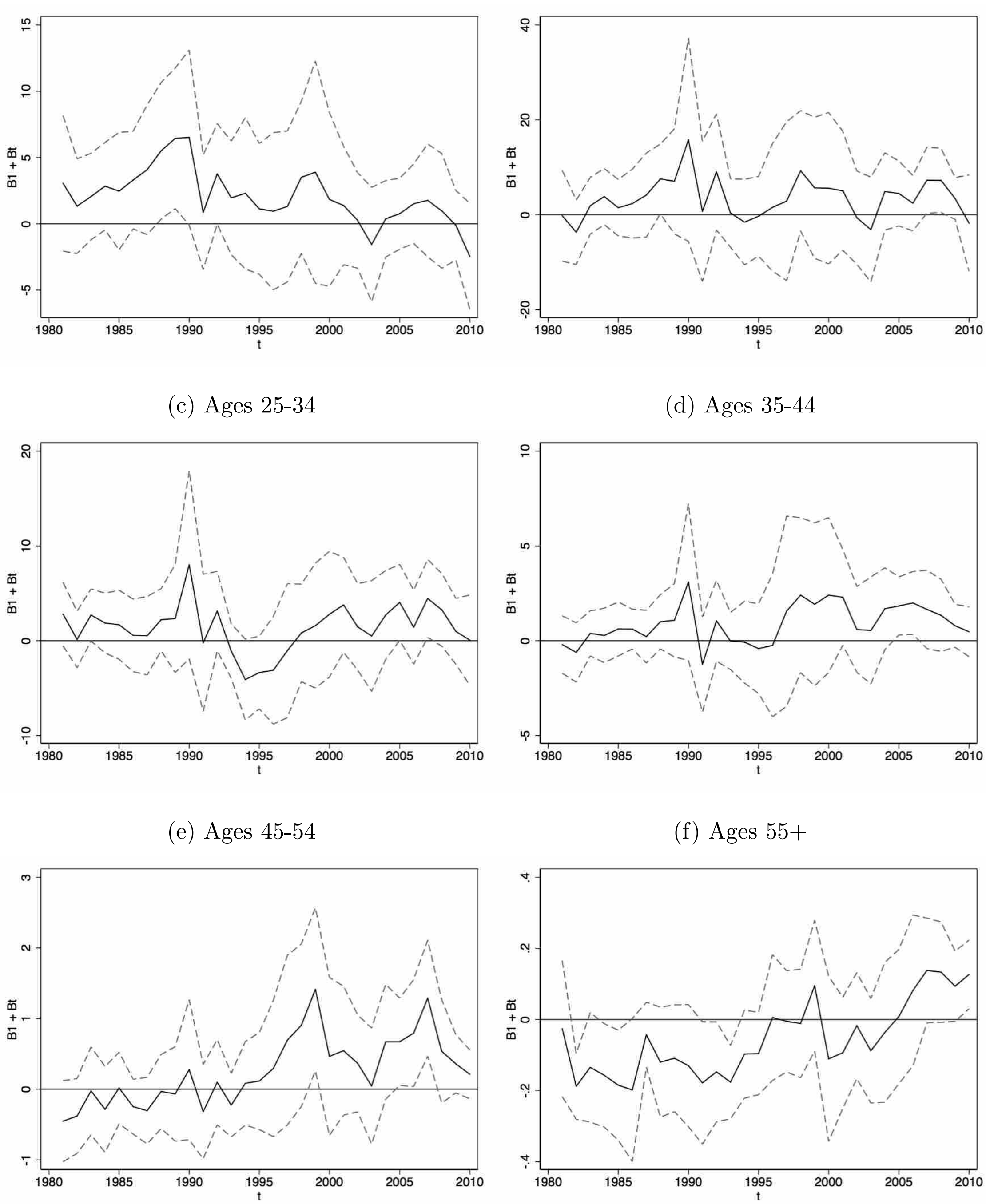


FIGURE 15. Annual Impact of Unemployment on Robbery By Age Group



(a) Ages 0-17

(b) Ages 18-24

(c) Ages 25-34

(d) Ages 35-44

(e) Ages 45-54

(f) Ages 55+

FIGURE 16. Annual Impact of Unemployment on Violent Crime by Age Group

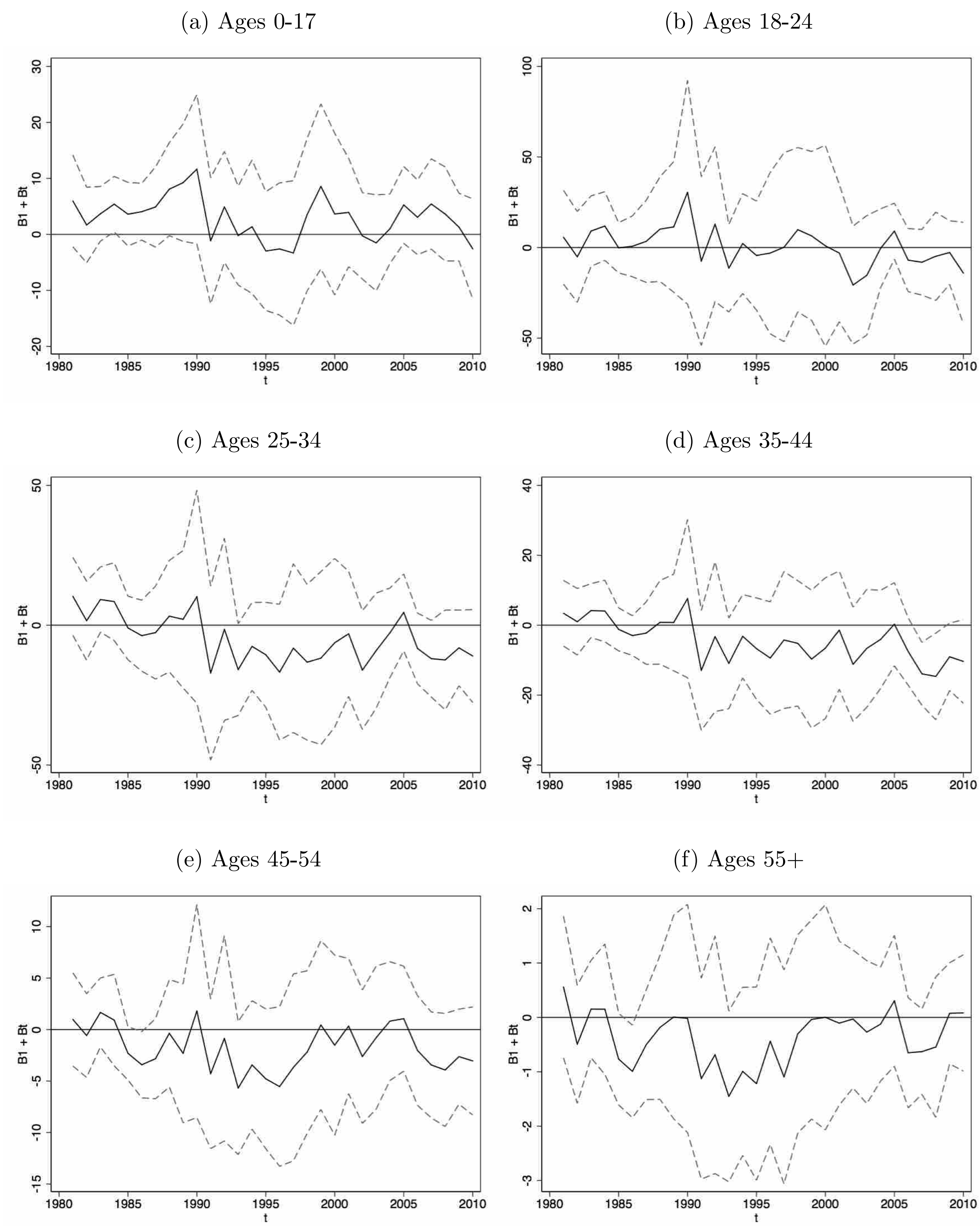
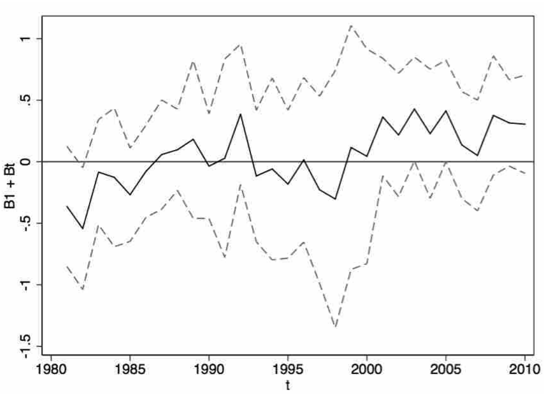
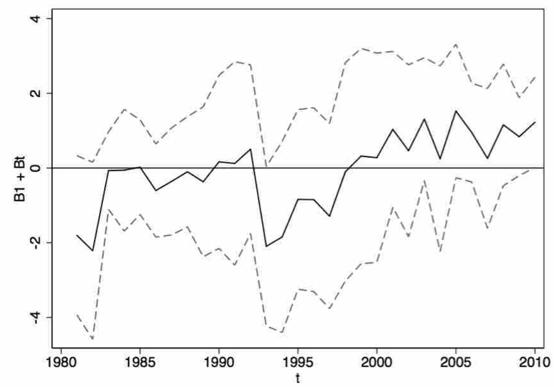


FIGURE 17. Annual Impact of Unemployment on Rape By Age Group

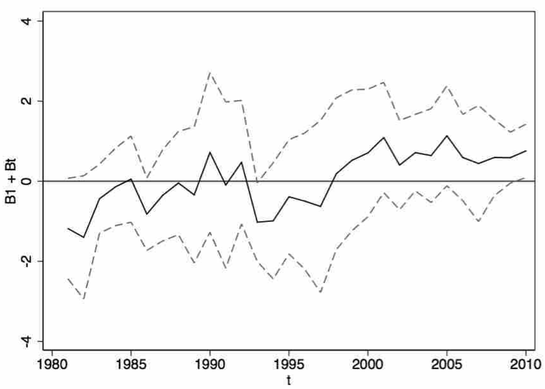
(a) Ages 0-17



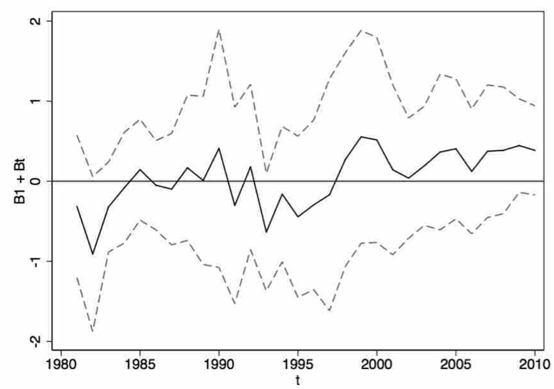
(b) Ages 18-24



(c) Ages 25-34



(d) Ages 35-44



(e) Ages 45-54

(f) Ages 55+

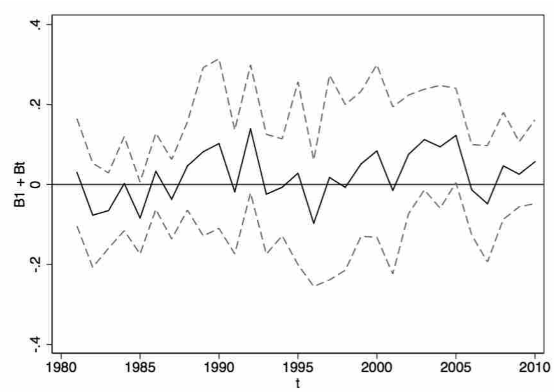
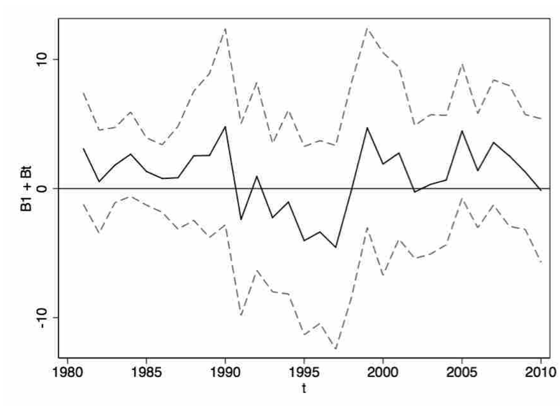
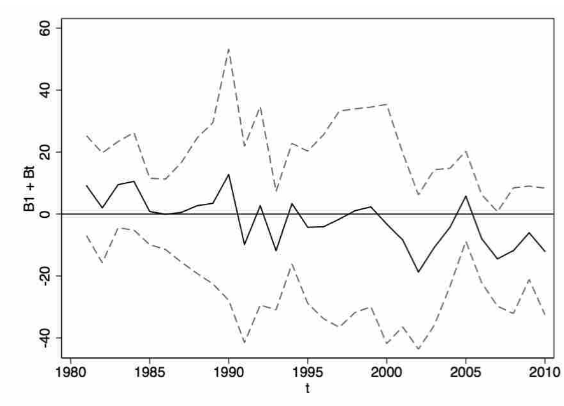


FIGURE 18. Annual Impact of Unemployment on Assault By Age Group

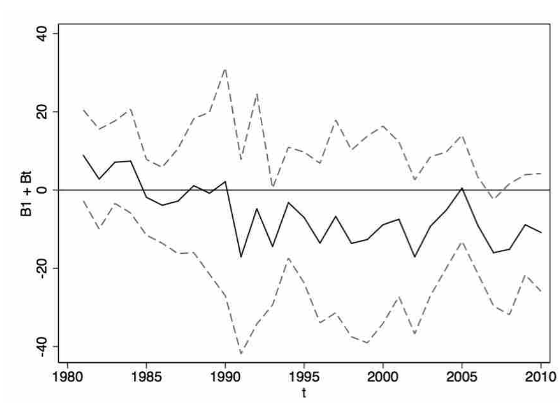
(a) Ages 0-17



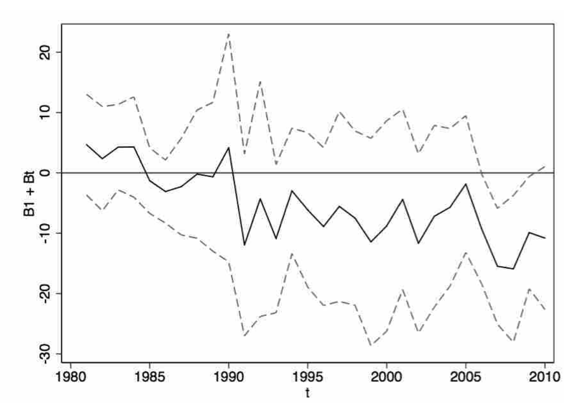
(b) Ages 18-24



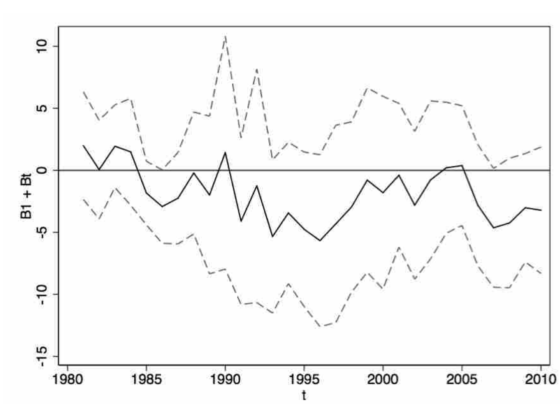
(c) Ages 25-34



(d) Ages 35-44



(e) Ages 45-54



(f) Ages 55+

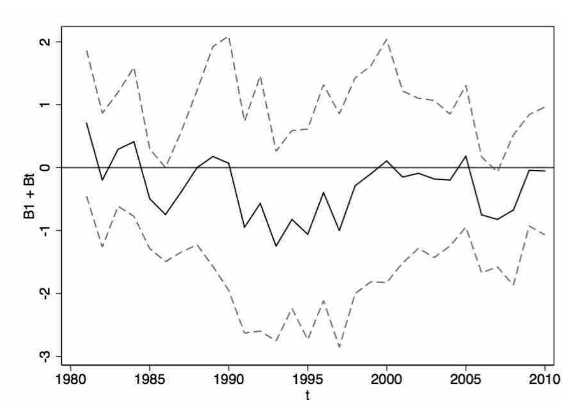
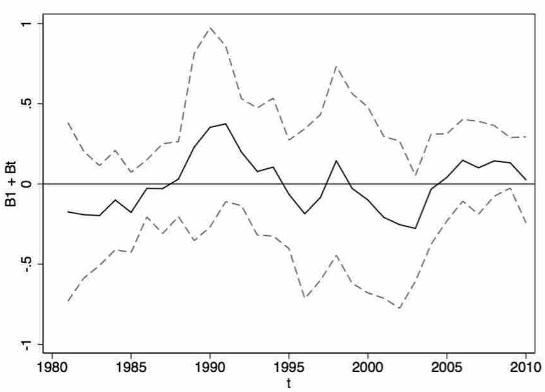
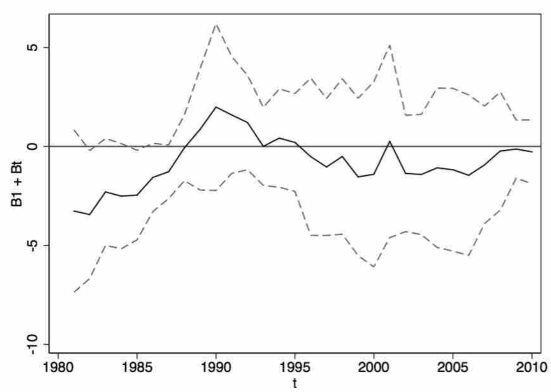


FIGURE 19. Annual Impact of Unemployment on Murder By Age Group

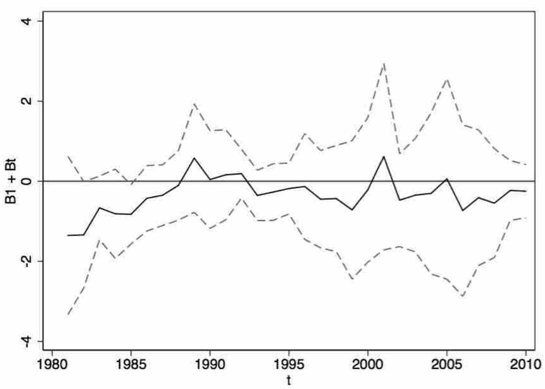
(a) Ages 0-17



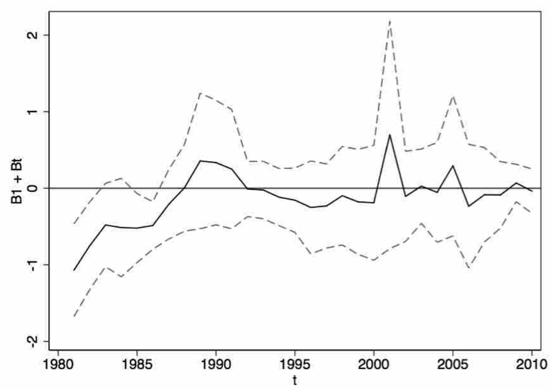
(b) Ages 18-24



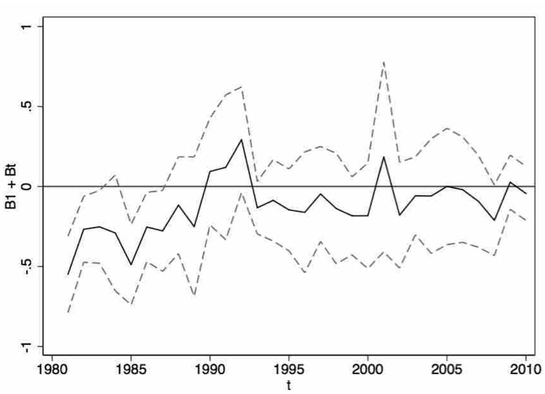
(c) Ages 25-34



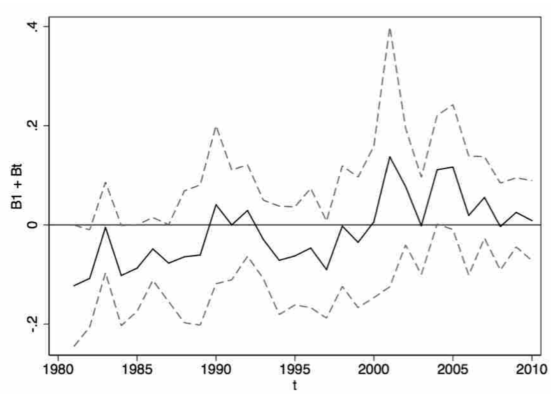
(d) Ages 35-44



(e) Ages 45-54



(f) Ages 55+



had estimates hovering around the constant-parameter. By the late 2000s, the estimated coefficient between unemployment and crime was not statistically different than zero for any age group.

For motor vehicle theft arrests, there was little difference in trends in age group parameters over time though there was substantial magnitude difference. During the 1980s and year 1990s, there is no evidence that any age group significantly responded to unemployment by stealing cars. However, in the late 1990s, individuals aged 18-54 were more likely to steal motor vehicles during periods of low unemployment. By the early 2000s, this trend had disappeared and during the Great Recession, each age group was more likely to steal cars (a reversal of signs). By 2010, all trends had reverted to zero.

Burglary arrest rates for ages 18-44 were significantly and positively related with unemployment within the constant parameter model. There is limited evidence that this parameter has greatly changed over the time sample. However, when allowing the parameter to be time varying, it becomes clear that during the late 1980s and 1990s that higher unemployment was also associated with higher rates of burglary among minors. Additionally, burglary arrests increased during the Great Recession for age groups 45-54.

There was no age group that experiences a significant increase in arrests for robbery in the constant parameter model. However, for minors, there was a significant positive relationship during the 1980s which diminished during the 1990s. For the oldest population, there was the reverse relationship with a negative coefficient during the 1980s which increased over time. By the Great Recession, arrest rates for robberies committed by individuals over the age 55 were significantly higher during periods of high unemployment.

As with robberies, there was no age group which significantly responded to unemployment by committing more rape crimes in the constant parameter model. While the parameter hovers around zero a good portion of the sample, for years 2000 and onward there appears to be a frequently significant positive relationship for minors and individuals aged 18-34.

For each age group, the impact of unemployment on aggravated assault crime rates was insignificant and around zero during the 1990s; however, there was a drop in the parameter estimate to a negative value for ages 25 and older in the years following. The standard errors on the estimate are noisy but the parameter follows a consistent trend during these years.

Lastly, I find that the significant and negative estimate on the effect of unemployment on murder crime rates for 35-54 year olds to actually be a remnant of a strong negative relationship during the 1980s. By the 1990s there was no significant relationship between unemployment and murder rates for any age groups.

Conclusion

Previous literature has often used long time series panel data to identify a relationship between unemployment and crime. This process neglects potential changes in the relationship of interest and effectively produces an average estimate. Consequently, this can identify a significant effect even if it has faded over time. If the parameter has indeed diminished, then the policy implications suggested by the time-invariant analysis are no longer applicable.

In this paper, I show that the responsiveness to unemployment has indeed changed over time. Repeating time-invariant regression procedures across small time samples suggests that this relationship has weakened for property crimes. I also allow for the parameter to vary over time using dummy variable methods and verify that the impact of unemployment on property crimes has diminished. In 1997, there was a notable decrease in the parameter estimate for the impact of unemployment on motor vehicle thefts and robberies. For burglary and larceny, the parameter diminished gradually. I also find evidence of non-zero impacts on violent crimes which has changed over the years. For murder and aggravated assault, in particular, arrest rates decreased during recessionary periods throughout the 2000s. The average effect is zero, which was the effect found in previous literature.

I further investigate heterogeneity in the effect of unemployment on crime by decomposing the effect by age group. Aggregate unemployment, as a measure for general economic conditions, are likely to impact certain age groups differently as incentives to commit crimes evolve throughout a person's life. I find that unemployment is most likely to affect crime rates for individuals aged 25 to 44. However, when the parameters are allowed to vary, I find that some groups which do not have a significant response to economic conditions in terms of crime, such as minors, experience periods in time where the relationship is non-zero.

I also investigate the heterogeneous impact of unemployment on crime rates across census regions. This potentially increases the precision of the estimated coefficient by artificially creating regions that more closely resemble one another in terms of norms and attitudes in regards to crime.[17] I find that Southern states only experienced increases in larceny during periods of high unemployment, where other regions experienced changes in other property and violent crime rates. When allowing the parameters to vary over time, there exists heterogeneous trend in the parameter across the region as well.

Taken together, the findings suggest that the relationship between unemployment and crime rates is not as clear and predictable as previously thought. External factors appear to be influencing this relationship and there is indication that during recent

[17] At the expense of loss of precision due to lower sample size.

years high unemployment is either not related or negatively related to property and violent crimes. This has direct implications for predictions from policies which affects unemployment, such as mass layoffs and prison releases. Moreover, it leads to the need to identify the source or sources of endogeneity which are affecting the parameter estimate. In doing so, the mechanism by which unemployment is affecting crime would likely become clearer.

Future research on this topic would seek to identify the source of of variation in this parameter. Papers addressing this topic should be cautious in examining the impact of economic conditions on different age groups, as the incentive to commit crime during recessionary periods greatly varies as a person ages.

In this chapter, I reopened the question of the impact of economic conditions on crime. Like substance abuse, crime rates disproportionately affect poorer regions in the United States. In developing countries, similar issues are at least as prevalent. Additionally, these regions struggle with satisfying day-to-day needs which is exacerbated by regional conflict, weather, and disease. Non-governmental agencies have been establishing financial groups in these regions to help individuals save and borrow funds to improve on these outcomes. In my next chapter, my coauthors and I develop a theory and explore the functioning of one type of financial group which has become increasingly popular and successful in developing countries around the world.

CHAPTER IV

THE ECONOMICS OF SAVINGS GROUPS

The theoretical model described in this chapter was developed by Andrea Canidio and Alfredo Burlando. These coauthors also contributed substantially to this work by developing and collecting experimental data from Ugandan savings groups and writing large sections of the paper. I performed the bulk of the data cleaning, was responsible for the development of empirical methods and analysis, wrote the sections on group functioning, comparison to other financial institutions, creating tables and figures for summary statistics and group behavior over time, and wrote the section on evidence for group behavior including all regression analysis and graphic production. All coauthors, myself included, collaboratively worked on the editing of this paper.

Introduction

Savings groups (SGs) are currently bringing financial inclusion to over 10 million poor households worldwide,[1] yet several important aspects of their functioning remain unclear. SGs are composed of twenty to thirty members who meet weekly, save with and borrow from the group over an operating cycle (usually lasting one year). At the beginning of the cycle, the group agrees on a set of rules which include the interest rate charged on disbursed loans. At the end of the cycle, the funds accumulated from savings and loan repayments are redistributed to group participants in proportion to how much each person saved, and the group may choose to start a new cycle.

[1] According to 2014 figures from the SEEP network, `www.seepnetwork.org/filebin/docs/SG_Member_Numbers_Worldwide.pdf`. This number considers only members of SGs formed and trained by large international NGOs, and does not include SGs formed by smaller organizations and independent agents, or spontaneously replicated groups.

Despite sharing some similarities with ROSCAS, credit unions, and microfinance, SGs have unique features distinguishing them from other group-based financial institutions. Savings groups participants, for instance, can utilize the funds available to smooth consumption, whereas ROSCA members are restricted to receiving a certain amount of funds at a specific date. In addition, for many of their members SGs are the only source of interest-bearing savings account and the only formal line of credit. Because SGs are designed to operate without the support of a financial institution, they can reach a population not reached by traditional microfinance interventions. Savings groups thus serve as a savings and lending institution that operates in the space between ROSCAs and microfinance, and require a separate understanding from either.

In this paper, we carefully describe the functioning of SGs, discuss the different types of SGs currently existing, and argue that SGs differ from other types of financial groups such as ROSCAs and credit unions. We then develop a theoretical model of an SG, which we use to highlight its most salient feature: the lack of a mechanism to ensure that the supply of funds equal its demand. Consequently lending may be rationed, in the sense that not all members wishing to borrow at a given interest rate may be able to do so. Importantly, when funds are scarce, there is no presumption that all members of the groups are affected equally: some members of the group may be able to fully satisfy their demand for loans while others are rationed out. If follows that groups may agree on rules that generate scarcity for a significant part of the cycle, provided that the "median" member is able to satisfy her demand for funds with these rules.

The possibility of scarcity gives rise to an externality problem, in that a member's borrowing and savings decisions affect other group participants. For example, an additional unit of savings contributed to the group in periods in which funds are scarce generates a positive externality, because this additional unit can be used to meet the demand for loans of others. However, an additional unit saved in periods in which funds are already abundant generates a negative externality, because this unit of savings is not lent out and only decreases the return on savings for all members. Thus, shocks affecting the borrowing and saving decisions of members can hurt or benefit the overall group. Interestingly, shifting savings from later periods to earlier periods always generates a positive externality on the other members of the group. This happens because early savings can be lent out during the first part of the cycle, and these loans generate resources that can be lent out again in subsequent periods.

In the last part of the paper, we use data from newly formed Ugandan savings groups to show evidence of fund scarcity. Our analysis of the weekly activity records indicates that loans are rationed for the first 80% of the cycle. Therefore our paper points to the importance of encouraging early savings. Theoretically, saving early rather than later has an unambiguous positive effect on the group; empirically, we find that the first part of the cycle is when finds are more likely to be scarce.

The remainder of the paper is organized as follows. The next section provides some background information on savings groups. Following this, we report some stylized facts about savings groups from our sample of Ugandan groups. We then develop a model of SG functioning and then provide evidence that savings groups operate under long periods of scarcity. The last section concludes with a discussion of the policy relevance of our results.

Background Information on Savings Groups

History and Existing Literature

The first savings groups were created in the early 1990s in Niger by CARE International and were called "Village Savings and Loan Associations" (VSLAs). Shortly after, several NGOs began promoting savings groups inspired by the VSLA model. The most popular alternative models are Savings and Internal Lending Communities (SILC) promoted by Catholic Relief Services and Oxfam's Saving for Change (SfC) groups. Despite the different names, all these savings groups operate under similar rules (see Table 19 for a comparison of the various models). Therefore, while the description of the functioning of savings groups in this paper most closely resembles VSLAs, we believe that our empirical and theoretical results apply to the most common types of SGs.

TABLE 19. Comparison of Different Types of Savings Groups

		*Group Type**	
	VSLA	**SILC**	**SfC**
Record Keeping System	Passbooks and balance reporting	Ledgers	Memorization or ledgers**
Member literacy essential?	No	No	No
Minumum ability for members and record keeper	Numeracy	Financial literacy	Numeracy
End of cycle distribution	Share-out based on amount saved	Share-out based on amount saved	Share-out based on amount saved
Social fund offered?	Yes	Yes	Yes
Security mechanism	Three-lock cashbox	Three-lock cashbox	Three-lock cashbox
Use of cashbox highly encouraged	Yes	Yes	Yes
Loan repayment time	Monthly	Monthly	Monthly
Application and approval process	Verbal	Verbal	Verbal
Number of members worldwide:	1,217,521	271,630	371,770
Number of countries:	26	26	5
Average members per country:	46828	10447	74354

Source: Allen and Panetta (2010)

* See below for a description of acronyms
VSLA: "Village Savings and Loan Asiciation" groups operated by CARE, Plan, or AKF
SILC: "Saving and Internal Lending Communities" groups operated by Catholic Relief Services (CRS)
SfC: "Saving for Change" groups operated by Oxfam/Freedom from Hunger (FFH)
** Groups outside of Mali use ledgers and declining balance system

Overtime, millions of members have joined these savings groups. Allen and Panetta (2010) reports data from groups formed by CARE International, Catholic Relief Services, and Oxfam, which together serve 1.86 million members. These groups are composed by a majority of women (between 70 and 80%), and are fairly stable (the retention rate across cycles is above 90%). Their members save between $12 and $27 on average (between 2.3 and 8.5 percent of national income per capita).

The development literature suggested that savings groups are an effective tool for local development (see Ashe and Neilan, 2003). Randomized evaluations of savings groups have shown that savings groups do indeed cause an increase in savings and borrowing, and improve food security, livestock holding and overall consumption smoothing at least in the short-run (Ksoll et al., 2015, Beaman et al., 2014, Gash and Odell, 2013, Banerjee et al. (2015)). A more recent strand of the literature focuses on the mechanisms internal to savings groups. Greaney et al. (2016) study the process of group formation, and compare the performance of groups formed and trained for free by NGO officers against the performance of groups formed by private trainers who charge fees. Cassidy and Fafchamps (2015) study the allocation of capital within groups, and find evidence that, due to the endogenous membership process, capital moves from those who demand savings to those who demand credit. Burlando and Canidio (2015) randomly assign members to groups with varying composition, and find that groups that are wealthier are better able to generate loanable funds, which are then lent to their poorest members.

Functioning

Group Formation Groups are typically formed through a guided process led by a trainer, or field officer. The trainer gathers a critical number of possible participants in a community, and then proceeds to explain the basic functioning of a SG. The community members who are interested in forming a SG undergo a training period, at the end of which a membership list is drawn and group operation starts. A group can have anywhere between 15 and 40 participants.

In many cases, trainers are employed by NGOs or by community-based organizations that specialize in financial intermediation. It is quite common to find that experienced savings groups members become trainers themselves, and start forming new groups in nearby communities.

Rule and Leadership Selection Operations of the group are governed by a *constitution*, which is typically adopted during the first meeting after the training period. This document specifies a number of rules, such as the length of the savings cycle, the interest rate charged on loans, the permissible savings amounts, the size and possible uses of an insurance fund. In addition, groups often adopt an extensive set of policies and procedures that govern how meetings are run, how collective decisions are taken or voted on, attendance policies, and a set of fines and fees sanctioning violators of rules.

The group also selects a number of group officials or representatives, which may include a chairperson and a treasurer.These officials ensure that accounts are kept correctly and group meetings proceed in an orderly fashion and according to the rules.

Savings At the beginning of each weekly meeting, each member saves with the group by *purchasing shares*. The share is a permissible and indivisible savings amount, and a member can typically purchase between zero and five shares per meeting. As such, the share value implicitly imposes an upper bound to the amount an individual can save within the group. Savings deposits are recorded in a group ledger and in an individual savings booklet. All cash deposits are pooled and kept in a metal safe box, which is opened only when the group is in session. Members are not allowed to withdraw their savings during the cycle.

Borrowing Funds that are accumulated in the safe box are made available to members of the group as interest bearing loans. Individual loans are extended to group members subject to three constraints: the group must agree on the stated purpose of the loan; loan sizes are restricted to three times the amount saved by the borrower until that point; and total loan disbursements should not exceed the amount available in the safe box. Within these conditions, multiple borrowers can obtain loans of varying sizes at the same time. Loans must be repaid within three months, and the interest on the principal compounds monthly. Once the loan is paid back, the borrower is eligible to borrow again. Borrowing starts three months after the beginning of the cycle. Three months before the end of the cycle, loan disbursements ends and all outstanding loans are repaid.

Insurance In addition to loan intermediation, most savings groups provide insurance as an additional financial service. Each member makes a required and fixed weekly contribution to an insurance pool. Typically, this contribution is small relative to savings.[2] Funds from the insurance pool are kept separate from the savings, and can be lent out to members in case of an emergency, such as funerals or severe illness. Standard repayment procedures are implemented, although no interest is collected on the emergency loan.

Accounting While individual members maintain their own passbooks, the group assigns a record keeper who maintains a log of individual savings, group cash in (savings, repayments, and fines), and loans serviced. The record keeper utilizes a *savings ledger* to record the total amount saved by each member in any given meeting. Also included in this

[2] In the savings groups we study, the value of the weekly insurance contribution is between one fourth of a share and one share.

ledger is a total savings balance amount. A *cash-book* is then updated with group-level balances at the end of the meeting (including carryover balances from previous meetings). All of these records are hand written and the record keeper is responsible for accurate calculations and reporting. This technique, however, does allow for human error (see Appendix A for a description of how we correct for these issues for the data used in this paper).

Share Out A unique feature of savings groups is their ability to provide positive returns on accumulated savings, which are realized at the end of the cycle in the process generally known as *share-out.* During share-out, the content of the safe box is emptied and divided among the members of the group in a way that is proportional to the amount each person saved. Hence, each member receives back everything he or she saved with the group, plus a fraction of the interest rate payments on loans. This fraction is equal to the amount saved by this person relative to total savings. More formally, if during weekly meeting t member i saves $s_{i,t}$, at share out she receives $(1 + R)\sum_t s_{i,t}$, where R is the returns on savings,

$$R = r\frac{\sum_i \sum_t b_{i,t}}{\sum_i \sum_t s_{i,t}},$$

r is the interest rate on loans and b_i is the cumulative amount borrowed by participant i.

Comparison to Other Financial Institutions

It should be readily apparent that savings groups share many features with financial institutions common in developing and developed countries alike.

SACCOs Savings groups are most similar to credit unions (commonly known as Savings and Credit Cooperative Societies or SACCOS in sub-Saharan Africa), in that they facilitate formal lending among the membership. However, savings groups are significantly less flexible than credit unions. Savings groups operate on short-term cycles, which prevents a sizable accumulation of capital; members are not allowed to withdraw savings during the cycle; interest rates are fixed and predetermined for all loans during the cycle; and the membership is quite small. Given these limitations, it is perhaps surprising that participation in SACCOS in Sub-Saharan Africa has been much more limited than participation in savings groups. For instance, in Uganda SACCOS participation is 3% of the population while membership in informal savings groups is 61% (FinScope (2010)). Reasons for differences in popularity require further research, although we speculate that the active participation of all members of a SG to its management is responsible for the popularity of SGs relative to SACCOS (where decisions are delegated to professional managers).

ROSCAs Other than credit unions, savings groups are often compared (and confused) with ROSCAs and self help groups. Like ROSCAs, savings groups pool savings from the membership on a weekly or monthly basis, and make those savings available to the group. A key difference with ROSCAs is the availability of a storage technology (a metal safe) and an accounting technology (book-keeping). Thus savings groups are much more flexible in the accumulation and use of their funds over time: group members are not required to save the same amount every period, multiple borrowers can borrow at the same time, and loan sizes can vary.

Self-Help Groups Self-help groups developed in India independently from Savings Groups. Similarly to savings groups, they collect savings from its members and distribute loans. However, they do not follow the rules of functioning of SG. In particular, they do not liquidate at the end of a cycle. Rather, the group distributes profits or dividends over time, and membership is allowed to vary.[3]

Some Stylized Facts

We now turn to the empirical analysis of the functioning of 110 newly-formed Ugandan savings groups.[4] This analyses is conducted using three primary sources of data. First, we collect *audit records* at shareout on all groups. These records contain: group-level characteristics; the cumulative amounts saved, borrowed, and repaid by each member; if the borrower was in arrears; and whether the member dropped out of the group during the evaluation period. This data set is the most comprehensive (includes information on all 110 groups). We then acquired *savings ledgers* recording the amount deposited by each member during each meeting and *cash-books* recording weekly cash inflows, outflows and balances from the same groups. These data sources turned out to be difficult to use (see Appendix 24 for more details), and we ended up with complete savings ledgers for 43 groups and complete cash books for 22 groups.[5]

We start by describing the end-of-cycle group savings and borrowing using the audit records for all 110 groups and how these figures compare to the Savix dataset (which is a repository of data from savings groups from all over the world). We then explore how the

[3]For more details see Allen and Panetta (2010), Ashe (2009), Vanmeenen (2010). Note that the distinction between self-help groups and savings groups described here is gaining popularity but is not universally adopted. For example, Greaney et al. (2016) study SILCs (which, according to our classification are savings groups) but call these groups "self-help groups". Blattman et al. (2015) also follow the same terminology when referring to VSLAs.

[4]These groups were formed in 2013 and were geographically dispersed throughout Uganda. See Burlando and Canidio (2015) for detailed information on these groups and on the data collection protocol.

[5]Groups also maintain loan ledgers, which keep record of all lending transactions and repayment histories. While we found that savings and cash ledgers are very standardized and were easily imported in an electronic database, loan ledgers were impossible to work with–we found that each group had their own recording standard for loans, and the records are often hopelessly confusing. For this reason, we have no individual level information on loans.

share price affects individual savings using the ledger data for the 43 groups. Lastly, we describe the evolution of funds over the course of a cycle using the cash-book data.

Savings Group savings and borrowing behavior is reported in Table 20.[6] Average cumulative savings is about $976 per group ($37 per member). The typical group and member savings for all CARE International savings groups (again from SEEP data) are also reported in this Table. It is clear that the audited groups saved only slightly less on average than other groups in Uganda.

TABLE 20. Summary Statistics from Audits of Ugandan Savings Groups and SAVIX

	Ugandan Savings Groups				*SAVIX Data**	
	Mean	Std. Dev.	Min	Max	Uganda VLSAs	All Africa VSLAs
Total Savings (USD)	975.63	383.86	176.32	2205.64	1,146.50	694.95
Average Amount Saved Per Member (USD)	36.88	15.47	6.08	81.69	39.60	27.62
Total Loans (USD)	1480.97	882.53	159.02	4122.90	-	-
Average Loans per Member	2.62	1.32	0.96	9	-	-
Average Amount Borrowed per Member (USD)	56.08	35.10	5.48	158.57	-	-
Loans-to-Savings Ratio	1.50	0.68	0.43	4.46	-	-
Outstanding Loans-to-Savings Ratio	-	-	-	-	0.97	0.93
Fraction of members with outstanding loans at shareout	0.03	0.08	0.00	0.40	-	-
Rate of return of savings	12.83	6.63	1.74	37.87	-	-
Number of Groups		110			8,188	49,795

* SAVIX data aquired from http://savingsgroups.com/analysis/

The amount of savings a member can accumulate is regulated by the share price. In our study groups, share values are quite low. All groups chose share values of 500, 1,000 or 2,000 UGX (approximately 19, 38 and 75 US cents in 2013 at the time). The implied ceiling of weekly savings is 93 cents, 1.88 dollars, and 3.75 dollars respectively. These small differences could amount to large differences in overall savings: Over a period

[6] All estimates are reported in USD$ using the conversion of 1 USD: 2,660 UGX.

corresponding to the median length of the cycle (47 meetings), a person who saves the maximum allowed would have been able to accumulate US$133 less in a group with a share value of 500 UGX than in a group with a share value of 2,000 UGX ($44 versus $176).

Table 21 reports group statistics at shareout by share price. It is clear that outcomes vary significantly with this price. Average savings at the end of the cycle was USD$28 (64% of the maximal limit) among 500 UGX groups, USD$38 (39% of the limit) among 1,000 UGX groups, and USD$62 (43% of the limit) among the 2,000 UGX groups.

We study in greater detail the constraints imposed by the share price by looking at person-meeting records from the 43 savings ledgers. In Table 22, we report the frequency that a particular number of shares was purchased in groups with a particular share price. The table reveals some interesting patterns. First, savings transactions often do not happen: members choose to save nothing 24% of the time in groups with "expensive" shares (2,000 UGX share value). The proportion is only slightly lower for groups with 500 UGX share value (21%), suggesting that the main difficulty facing participants is coming up with *any* savings for the meeting (or coming to the meeting itself), rather than meeting the minimum savings threshold. Secondly, the upper limit on savings imposes a real constraint on savings. This can be seen by the proportion of transactions that involve the purchase of 5 shares. In our sample, 48% of transactions in 500 UGX groups, 30% in 1,000 UGX groups, and to 23.5% for 2,000 UGX groups fall into this category. Finally, the table indicates that the distribution of savings is bimodal throughout. In 500 UGX groups, most transactions are either zero or 5 shares; at the other extreme, in 2,000 UGX groups transactions are either at zero or one share, or 5 shares.

Borrowing Table 20 also includes information on group borrowing. On average members took out about 2.6 loans totaling approximately USD$56 over the course of the

TABLE 21. Summary Statistics from Audits of Ugandan Savings Groups (By Share Value)

	Mean	Std. Dev.	Min	Max	Number of Groups
Price = 500					
Total Savings (USD)	762.08	278.43	176.32	1171.81	28
Average Amount Saved Per Member (USD)	28.18	10.44	6.08	44.39	28
Total Loans (USD)	1406.72	953.79	159.02	4122.90	28
Average Loans per Member	3.02	1.61	1.04	9	28
Average Amount Borrowed per Member (USD)	51.85	35.51	5.48	158.57	28
Loans-to-Savings Ratio	1.75	0.78	0.57	3.79	28
Average Annualized Rate of Return	15.15	9.04	2.87	37.87	28
Price = 1000					
Total Savings (USD)	1027.42	389.03	280.08	2205.64	77
Average Amount Saved Per Member (USD)	38.41	15.11	7.78	81.69	77
Total Loans (USD)	1500.14	866.62	259.40	3644.74	77
Average Loans per Member	2.53	1.21	0.96	7	77
Average Amount Borrowed per Member (USD)	56.39	34.22	7.86	151.86	77
Loans-to-Savings Ratio	1.43	0.62	0.58	4.46	77
Average Annualized Rate of Return	12.10	5.32	1.74	26.37	77
Price = 2000					
Total Savings (USD)	1373.99	217.66	1212.03	1739.10	5
Average Amount Saved Per Member (USD)	62.07	9.16	47.73	72.14	5
Total Loans (USD)	1601.43	865.98	560.15	2599.25	5
Average Loans per Member	1.83	0.51	1.37	3	5
Average Amount Borrowed per Member (USD)	75.10	47.12	20.75	144.40	5
Loans-to-Savings Ratio	1.18	0.69	0.43	2.14	5
Average Annualized Rate of Return	10.89	7.52	3.56	21.45	5

cycle (an average of $1,480 per group). Clearly this is substantially more than savings per member and is the result of frequent repayment of these interest-bearing loans. By the end of the cycle, individuals saw an average rate of return on savings of about 12.83% and a ratio of cumulative loans to cumulative savings of about 1.5.[7] Finally, we note that

[7]Among a subsample of 780 study participants, the single most common use (44% of loans and 39% of share out) is the payment of school fees. In addition, 35% of loans and 40% of share out amounts are used for some type of productive investment, including starting a new business, purchasing of farm inputs such

TABLE 22. Tabulation of Weekly Share Purchases of Individual Borrowers (44 groups)

	Share price =500		Share price=1,000		Share price=2,000	
Share purchase	Freq.	Percent	Freq.	Percent	Freq.	Percent
none	3,294	21.51	8,422	23.94	1,275	24.23
1 share	374	2.44	4,474	12.72	1,422	27.02
2 shares	2,188	14.28	6,119	17.39	417	7.92
3 shares	529	3.45	2,823	8.02	286	5.44
4 shares	1,610	10.51	1,717	4.88	153	2.91
5 shares	7,315	47.76	10,488	29.81	1,237	23.51
Other amount	7	0.05	1,143	3.25	472	8.97
Total	15,317	100	35,186	100	5,262	100

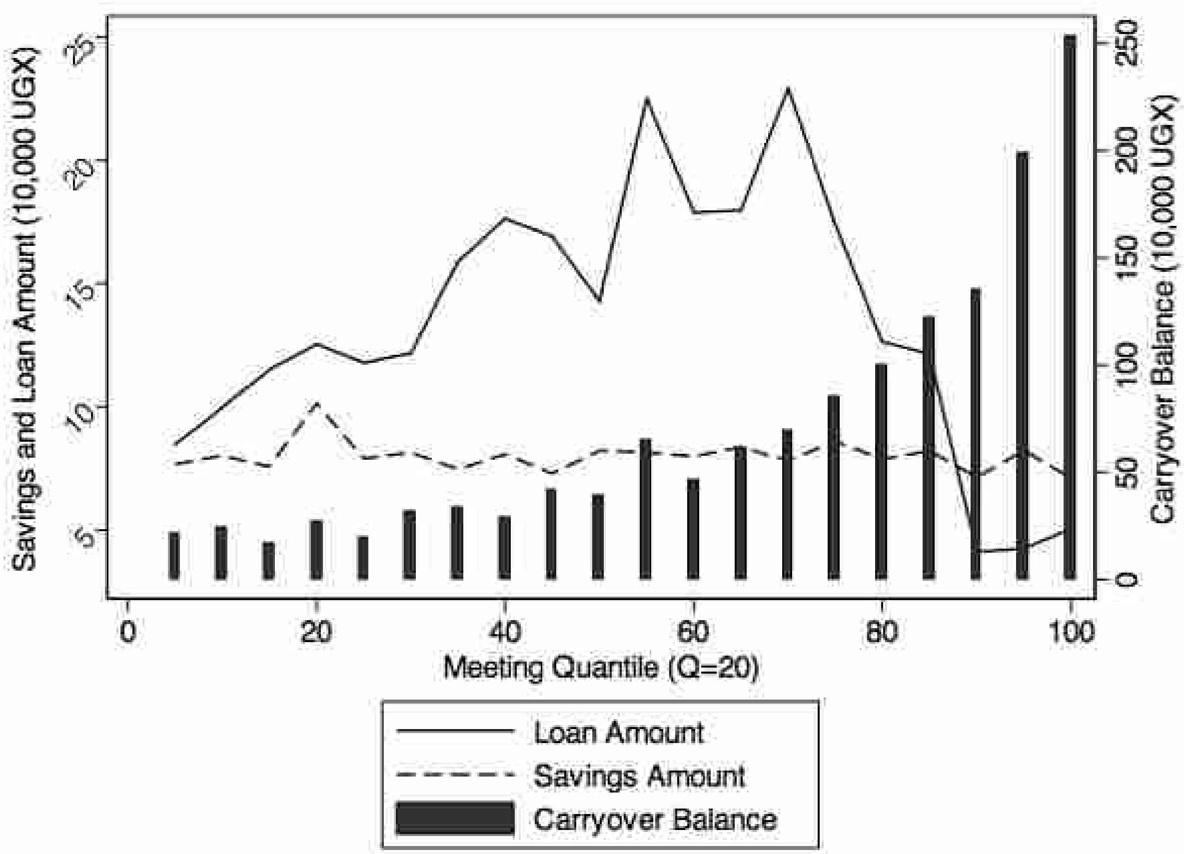
defaults on loans are rare: only 3% of members were reported not having paid the whole loan by shareout.

As with savings, borrowing behavior and savings returns depend on the share price chosen by groups. As seen in Table 21, lower share prices tended to have slightly smaller but more frequent loans per member, lower total group borrowing. However, we see that the smallest share price (500 UGX) experienced the highest loans-to-savings ratio and return on savings which is suggestive that these groups are lending a larger portion of their available funds throughout the cycle.

Balances Over Time We finally provide a dynamic view of group operations by making use of the cashbook data. Figure 20 plots the evolution of cash balances, per-period savings and loans disbursed in a sample of 22 Ugandan savings groups. Saving contributions remain quite stable over the duration of the cycle, whereas loans grow over time and peak towards the end of the cycle. On average, balances remain close to zero for

as livestock and land, or other business investment. Loans are somewhat more likely than share out to be used for emergencies, such as a health incident or unemployment (22% versus 16%.). Conversely, and quite predictably, households are almost twice as likely to consume their share out (29%) than their loans (16%). See Burlando and Canidio (2015) for further details.

FIGURE 20. **Saving, borrowing, and cash-in-box over the cycle.** Data from 22 savings groups with complete records of all financial transactions. Length of the cycle normalized to twenty quantiles (x axis). Left axis is the scale for flow variables (savings and loans per meeting); right axis is scale for stock variables (carryover balance), which we refer as "cash in the box".



almost half of the cycle, suggesting that groups are unable to generate sufficient funds to meet the demand for loans of their members. We formally test for the presence of funds scarcity using these data in a later section.

A Model of Savings Groups

In this section we present a theoretical model of SG. Our goal is to discuss how SG rules determine the individual incentive to save and borrow, and to show that funds may be in excess or fall short of the demand for loans. We abstract away from other potential sources of inefficiencies such as moral hazard, adverse selection, behavioral biases, voluntary or involuntary defaults (which, as we previously discussed, are a rare occurrence in our data).

Consider a group composed of n individuals. The timing of the game is the following:

- In period 0, the group meets and agrees on the interest rate that will be charged on loans r and on the maximum savings per period $\overline{s}$. As previously discussed, the maximum savings per period is implicitly determined by the share value chosen by the group. Here, we abstract away from the fact that savings are allowed only in multiples of the share values. As a consequence the only role of the share value is determining $\overline{s}$.

- In periods 1 to $k > 1$ each member i:

    * first receives $w_{i,t}$, which is a per-period wage (i.e. non-investment income generated outside of the group),

    * then saves $s_{i,t}$ with the group,

    * then borrows $b_{i,t}$ from the group,

    * then invest $y_{i,t}$ in an outside project,

    * then earns $f_{i,t}(y_{i,t})$ from the funds invested outside of the group, where $f_{i,t}()$ is continuous and strictly concave.[8]

    * repays $(1 + r)b_{i,t}$ to the group, saves $a_{i,t} \geq 0$ outside of the group, and consumes the rest.

[8]The assumption of concavity allows us to show the existence of the equilibrium of the game. The reason is that, if $f_{i,t}()$ is locally convex, then optimal savings and borrowing may be a non-convex correspondence, which prevents us from invoking standard fixed point theorems,

Given this sequence of events, a single period of our model is better interpreted as 3 months, which is the duration of each loan.

- In period $k+1$, the money collected by the group is redistributed to members in proportion to the amount saved by each.

Both $f_{i,t}(y_{i,t})$ and $w_{i,t}$ are deterministic. Finally, by assuming that the return on the outside project $f_{i,t}(y_{i,t})$ is independent on the group composition, we are effectively ignoring other relevant channels through which the group may impact the return on investment, such as learning from peers, changes in the social network structure, and aspirations.

Independently on the rules agreed upon in period 1, no member is allowed to borrow more than 3 times the total amount saved with the group up until that period, and therefore

$$b_{i,t} \leq 3 \sum_{x=1}^{t} s_{i,x} \quad \text{for } t \in \{1, .., k\}, \tag{4.1}$$

which we call the *leverage constraint.* In addition, the agent can save with the group up to $\overline{s}$, so that:

$$s_{i,t} \leq \min\{w_{i,t} + a_{i,t-1}, \overline{s}\}, \tag{4.2}$$

where we assume $a_{i,0} = 0$, so that the resources available for saving are $w_{i,1}$ in period 1, $w_{i,1} + a_{i,1}$ in period 2, and so on.[9] Note that the timing described above implies

$$y_{i,t} \leq b_{i,t} + w_{i,t} - s_{i,2} + a_{1,t-1} \quad \text{for } t \in \{1, .., k\}. \tag{4.3}$$

In other words, the resources available for investment are equal to own funds (either earned during that period $w_{i,t}$ or carried from the previous period $a_{1,t-1}$) minus the

[9]We implicitly assume that the resources saved outside of the group do not generate any return.

savings with the group, plus borrowing with the group. Finally, consumption at the end of each period is:

$$c_{i,t} = f_{i,t}(y_{i,t}) - y_{i,t} - rb_{i,t} + w_{i,t} + a_{i,t-1} - a_{i,t} - s_{i,t} \geq 0, \tag{4.4}$$

which is the agent's *budget constraint*.

Individual Maximization Problem At the beginning of each period of operation of the group, a member i decides how much to save and borrow with the group by maximizing her utility, taking as given the assets accumulated outside of the group $a_{i,t}$, and the savings previously accumulated with the group $\sum_{x=1}^{t-1} s_{i,x}$. This problem can be expressed in recursive form:

$$V_{i,t}\left(a_{i,t}, \sum_{x=1}^{t-1} s_{i,x}\right) = \max_{b_{i,t}, s_{i,t}, y_{i,t}, a_{i,t}} \left\{u_i(c_{i,t}) + \beta_i V_{i,t+1}\left(a_{i,t+1}, \sum_{x=1}^{t} s_{i,x}\right)\right\}$$

$$\text{s.t.} \begin{cases} b_{i,t} \leq \tilde{C}_{i,t} & \text{aggregate resource constraint} \\ \text{equations 4.1 to 4.4} & \end{cases}$$

with the utility at share out:

$$V_{i,k+1}\left(a_{i,k}, \sum_{x=1}^{k} s_{i,x}\right) = \left(\sum_{x=1}^{k-1} s_{i,x} + s_{i,k}\right)(1+R) + a_{i,k}.$$

where $\beta_i \in (0,1)$ is agent i discount factor, and $u_i(.)$ is agent i utility from consumption, strictly increasing and strictly concave. Note that in the above specification implies that the agent's utility function is linear in the money received at share out.[10]

[10] All results derived are robust to a utility function that is curved in money, provided that the curvature is not too strong.

The term $\tilde{C}_{i,t}$ is the cash available to member i of the group at the beginning of each period, defined as

$$\tilde{C}_{i,t} = S_t + \sum_{x=1}^{t-1}(S_x - B_x) + (1+r)\sum_{x=1}^{t-1} B_x - \sum_{j \neq i} b_{j,t} \tag{4.5}$$

where $B_x = \sum_i b_{i,x}$ and $S_x = \sum_i s_{i,x}$ are aggregate borrowing and savings in period x. In other words, the cash available for borrowing to agent i in period t is given by the sum of all excess savings (aggregate savings minus aggregate borrowings) plus the loans repayments collected by the groups from period 1 to t, minus period-t loans given to all other members. The term R is the implicit return on savings, defined as

$$R = \frac{r \cdot \sum_{t=1}^{k} B_t}{\sum_{t=1}^{k} S_t}$$

We conclude the description of the model by introducing our main assumption:

Assumption 1. *The return on savings at the end of the cycle R and the funds available to each member of the group in each period $\tilde{C}_{i,t}$ are taken as given by the group members but are determined in equilibrium.*

In other words, the group members fail to anticipate that by increasing the amount saved (or borrowed) they will affect the return on savings and the availability of funds for the entire group. As a consequence, we can treat the return on savings and the funds available to the group in each period as equilibrium quantities.[11]

[11] Given that the group is large, the incentives to influence the return on savings by setting a specific s_i or b_i are likely to be negligible. Note also that all our results are robust to assuming that the aggregate resource constraint is $b_{i,t} \leq \alpha_i s_{i,t} + \tilde{C}_{i,t}$, and $\tilde{C}_{i,t} = S_t + \sum_{x=1}^{t-1}(S_x - B_x) + (1+r)\sum_{x=1}^{t-1} B_x - \sum_{j \neq i} b_{j,t} + (1-\alpha)s_{i,t}$, where α_i is the amount of an agent's own savings that this agent expects to be able to borrow back from the group. The parameter α_i should depend on the rationing mechanism employed by the group (discussed in a later section on rationing).

Individual Saving and Borrowing Decision

Call $s_{i,t}(r, R, \tilde{C}_{i,t})$ the optimal savings and $b_{i,t}(r, R, \tilde{C}_{i,t})$ optimal borrowings of agent i in period t.

Lemma 1. *$s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$ are upper hemicontinuous in r, R and $\tilde{C}_{i,t}$. In addition, $s_{i,t}(r, R, \tilde{C}_{i,t})$ is weakly increasing in R. If the aggregate resource constraint is binding, $s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$ are weakly increasing in $\tilde{C}_{i,t}$. If the aggregate resource constraint is not binding, $s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$ are independent on $\tilde{C}_{i,t}$.*

We complement the above lemma with a remark that follows from inspecting the individual maximization problem:

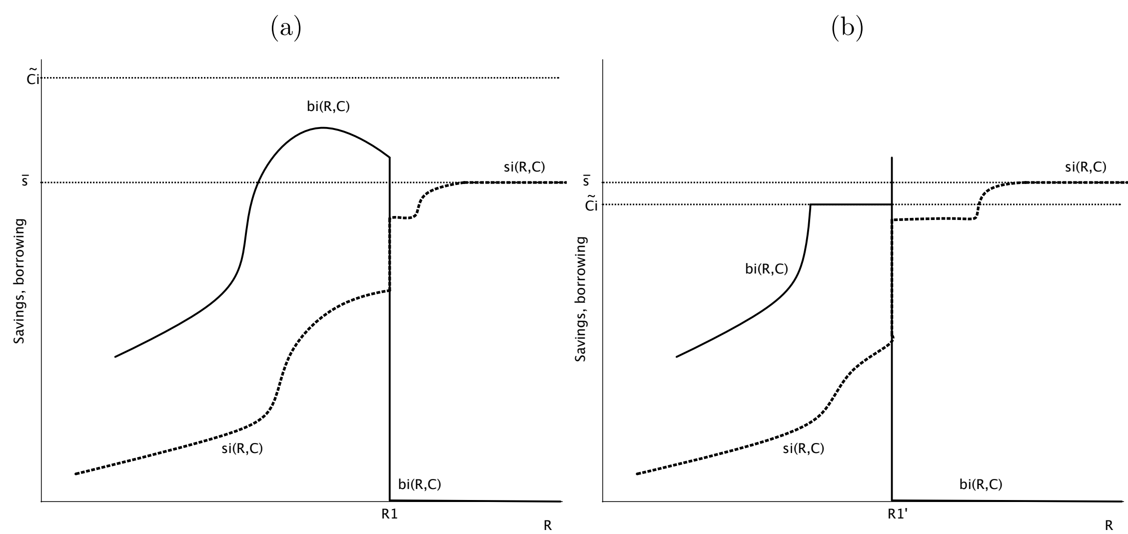
Remark 1. *The cost of borrowing is decreasing in R. Conditional on being a borrower, $b_{i,t}(r, R, \tilde{C}_{i,t})$ is weakly increasing in R. However for R sufficiently large, the agent may set $b_{i,t}(r, R, \tilde{C}_{i,t}) = 0$ and only save.*

Because of the leverage constraint (Equation 4.1), a member who wishes to borrow must first save. Hence, as the return on these savings increases, the cost of borrowing decreases. This reduction on the cost of borrowing weakly increases the amount saved (by Lemma 1) and the amount that can be borrowed (by Equation 4.1). This is achieved by reducing the fraction of a project that is self financed, and increasing the scale of the investment. However, if R increases sufficiently, then the agent may switch from being a net borrower to being a net saver. This possible "jump" from borrower to saver is the reason why the amount borrowed and saved may be discontinuous in R. In case of discontinuity, $s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$ are nonetheless upper hemicontinuous: if two borrowing (savings) levels solve the utility maximization problem, then any convex combination of the two also solves the utility maximization problem. In other words, the savings and borrowing correspondences have no "holes".

Figure 21 illustrates a possible $s_{i,t}(r, R, \tilde{C}_{i,t})$ and a possible $b_{i,t}(r, R, \tilde{C}_{i,t})$ for the same agent in two situation: one in which the aggregate resource constraint is never binding (left panel), the other when it sometimes is (right panel). For low and high R, the two panels are identical because borrowing is either too low or zero, so that the upper bound $\tilde{C}_{i,t}$ is not reached. For intermediate R's instead, the two panels are different. Relative to the left panel, in the right panel borrowing is constrained by $\tilde{C}_{i,t}$ and, as a consequence, savings is also depressed.

We conclude by pointing out two additional results. First, note that the scarcity of funds may not impact all group members equally. It may be the case that the aggregate resource constraint is binding, but some members can fully meet their demand for loans while the burden of rationing falls disproportionately on others. We say that a member

FIGURE 21. **Individual savings and borrowing choices:** In Panel (a), the aggregate resource constraint is never binding. In Panel (b), the aggregate resource constraint may be binding. In both cases, demand b_i and supply s_i are initially increasing with the return on savings R, although savings $s_{i,t}$ is capped at $\bar{s}$. Below R_1 and R'_1 savings and borrowings are positive. Above R_1 and R'_1 the borrower switches to savings only. In addition, in Panel (b), the amount that can be borrowed has an upper bound $\tilde{C}_i$. The constraint shifts the savings curve downward whenever it is binding, and savings and borrowing choices are now lower than when in the left panel. While the savings decision at high levels of savings is not affected by the constraint, whenever the constraint is binding the borrower may switch to zero borrowings at lower values of R. Hence $R_1 \geq R'_1$.



is *rationed out* in period t if her demand for loans is strictly increasing in $\tilde{C}_{i,t}$. Second, given the generality of the individual maximization problem, we do not link individual characteristics of each group member to a precise borrowing and savings behavior. In what follows, we characterize each member of the group directly by her $s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$, under the restriction that these functions satisfy Lemma 1 and Remark 1.

Rationing Mechanism

Before solving for the equilibrium of the model, we need to discuss how $\tilde{C}_{i,s}$ is determined. We assume that in each period, after the savings decisions are made, each member of the group announces her demand for loans, and the group determines each $\tilde{C}_{i,t}$ according to a *rationing mechanism*. We also assume that the rationing mechanism adopted by the group is:

– Resource monotonic: for given r, $\overline{s}$ and R, increasing the funds available to the group weakly increases the amount borrowed by each member,

– Pareto efficient: the allocation of funds induced by the mechanism is never Pareto dominated by another feasible allocation,

– Strategy-proof: no member has an incentive to misreport her demand for funds.

A large literature has investigated allocation mechanisms in the context of single peaked preferences. One mechanism often highlighted is the so-called *uniform rule*. This rule amounts to imposing an upper bound on the level of borrowing achievable by each member. If any member borrows less than the upper bound announced (because her peak is below the upper bound), the remaining resources are distributed among the other members using again the same mechanism. Kıbrıs (2003) considers an allocation problem with single peaked preferences and free disposal (i.e. not all resources need to be allocated), and shows that the uniform rule is the only strategy-proof mechanism that satisfies efficiency, no-envy, and is resource monotonic.[12] In our context, preferences are single peaked over $b_{i,t}$ (and the results in Kıbrıs, 2003, apply) because the return on the outside investment $f_{i,t}(y_{i,t})$ is strictly concave for all i and t.[13]

Note, however, that the uniform rule has very appealing properties *for given savings contributions*. It is unclear whether the uniform rule maintains its properties once we take into consideration that savings depend on the rationing rule. More theoretical work is needed to characterize the set of optimal rationing mechanisms in savings groups. For this reason, in what follows we simply assume that the rationing mechanism is resource monotonic, efficient and strategy-proof for given savings contribution. Hence, for the most part we will abstract away from the specific rationing mechanism employed by the group. An exception will be discussed in a later section, where we solve for the period-0 choice of r and $\overline{s}$, because the "median" member of the group will depend on the rationing rule in use.

Equilibrium

Despite being taken as given by the group's members, R and $\tilde{C}_{i,t}$ are determined in equilibrium. In particular, the equilibrium $R \equiv R^{\star}$ solves:

$$R^{\star} \sum_{t=1}^{k} S_t(R^{\star}) = r \sum_{t=1}^{k} B_t(R^{\star}) \tag{4.6}$$

[12] A rationing rule satisfies no-envy if for every announcement profile, the allocation implemented by the mechanism is such that no group member wants to swap what she received with what some other group member received. For a review of this literature and the formal definition of these properties, see Thomson (2014).

[13] A second widely studied mechanism is *serial dictatorship*, in which members take turns in choosing their optimal borrowing amount until no funds are left. In Appendix B we argue that this rationing rule may be resource monotonic, Pareto efficient and strategy-proof in situations in which the uniform rule fails to satisfy these properties.

where $S_t(R)$ and $B_t(R)$ are the aggregate demand and supply of funds in period t.

Note that, whereas the individual demand and supply of funds depend both on R and on $\tilde{C}_{i,t}$, the expressions for the aggregate demand and supply for funds only depend on R (we omit the dependency on r). The reason is that, in the individual maximization problem, $\tilde{C}_{i,t}$ matters only if the aggregate resource constraint is binding. Furthermore, because the rationing mechanism is Pareto optimal, the aggregate resource constraint is either binding for everybody or not binding for anybody. Therefore, in the aggregate we can simply distinguish between R for which the aggregate resource constraint is binding and R for which the aggregate resource constraint is not binding during a given period. Whenever the aggregate resource constraint is not binding, aggregate borrowing depends on aggregate savings only through the equilibrium $R^{\star}$. Instead, in periods in which the aggregate resource constraint is binding, aggregate borrowing depends on aggregate savings directly. In particular, when the resource constraint is binding in a given period, $b_{i,t} = \tilde{C}_{i,t}\ \forall i$, and by Equation 4.5:

$$B_t(R) = r \sum_{x=1}^{t-1} B_x(R) + \sum_{x=1}^{t} S_x(R). \tag{4.7}$$

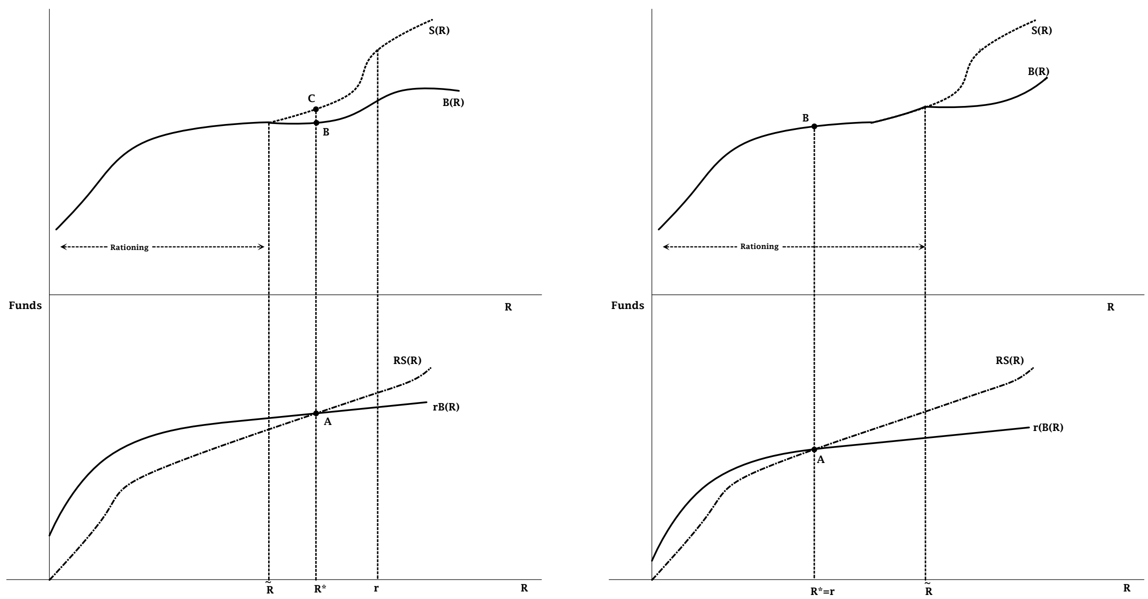
Hence, in periods in which funds are scarce, aggregate savings and aggregate borrowings are perfectly correlated. This observation will play a central role in the next section, where we empirically address the issue of funds scarcity.

Figure 22 provides an illustration of the equilibrium, for the case in which the aggregate borrowing and savings are continuous functions and the group is active in only one period (i.e., $k = 1$). The left graph presents the case where the resource constraint in binding, and the right graph the case where it is not binding. In each case, the top panel provides a description of the behavior of the supply curve $S(R)$ and demand curve $B(R)$

FIGURE 22. **Two examples of a unique equilibrium when $k = 1$.** In both cases the equilibrium $R^\star$ is determined in the bottom panel by the intersection of $RS(B)$ and $rB(R)$.

(a) **No rationing in equilibrium.** The equilibrium occurs at point A. As shown by points B and C $S(R^*) > B(R^*)$. It follows that $R^* < r$.

(b) **Rationing in equilibrium.** For $R < \tilde{R}$, funds are rationed and supply of funds is equal to demand: $S(R) = B(R)$. Because the equilibrium (point A) occurs on the rationing area, $S(R^*) = B(R^*)$ and $R^* = r$.



with respect to the realized rate R. The bottom panel describes the behavior of the two curves $RS(R)$ and $rB(R)$.

Distinguishing between periods in which the aggregate resource constraint is binding or not will be relevant when performing our comparative statics analyses. For example, assume that a member of the group drops out and is replaced by another person with a higher propensity to save in every period and at every R.[14] If the resource constraint is never binding, we can solve for the new equilibrium simply by shifting

[14]If the rules of the group are chosen by majority voting, then changing the composition of the group does not affect the rules adopted by the group as long as the median member of the group does not change. Hence, we can analyze changes in the demand and supply of funds due to a change in the group's composition keeping the rules adopted by the group constant.

upward $\sum_{t=1}^{n} S_t(R^\star)$. If instead the aggregate resource constraint is binding in some periods, then aggregate borrowing in these periods will also respond to an increase in overall funds available to the group.

We now provide an important result of our framework: that an equilibrium R^* always exists. We also derive a sufficient condition for an unique equilibrium, which we will use in comparative statics.

Proposition 1. *An equilibrium $R^\star$ always exists. If β_i is sufficiently small for all i, then the equilibrium is unique. Assuming that at the unique $R^\star$ both $\sum_t S_t(R)$ and $\sum_t B_t(R)$ are functions, then the LHS of equation 4.6 crosses the RHS of equation 4.6 from below.*

Note that β_i determines the sensitivity of the borrowing decision to the return on savings. If this sensitivity is low the cost of borrowing is determined mostly by r and not by R. Hence, as β_i decreases, the elasticity of aggregate borrowing with respect to R decreases, and multiple equilibria disappear. In what follows, we always assume that $R^\star$ is unique for all r and $\overline{s}$.

Comparative Statics

Using proposition 1 and assuming that the equilibrium is unique, we next analyze the effect of changes in the demand or the supply of funds in these groups.

Increase in Aggregate Savings Suppose that the aggregate savings increases in all periods. This could be the case if a member of the group who only saves drops out of the group and is replaced by another agent who also only saves but has a larger propensity to save at every r, R and $\tilde{C}_{i,t}$. Clearly, if the resource constraint is never binding, then, for given R, the increase in aggregate savings has no effect on aggregate borrowing. Hence, the behavioral responses of the group members is driven by the fact that, by proposition 1, when $\sum_t S_t(R)$ shifts upward $R^\star$ decreases.

Corollary 1. *Suppose that the aggregate resource constraint is never binding. Furthermore, suppose that there is a change in the behavior of one of the group members, leading to an upward shift in $S_t(R)$ (for some t). As a consequence, $R^\star$ decreases and everybody else in the group is worse off.*

If instead the aggregate resource constraints is always binding, adding resources to the group has also a direct effect on the borrowing levels that are possible within the group.

Corollary 2. *Suppose that the aggregate resource constraint is always binding. Furthermore, suppose that there is a change in the behavior of one of the group members, leading to an upward shift in $S_t(R)$ by the same factor in every period t. Each member's borrowing (weakly) increases and everybody else in the group is (weakly) better off.*

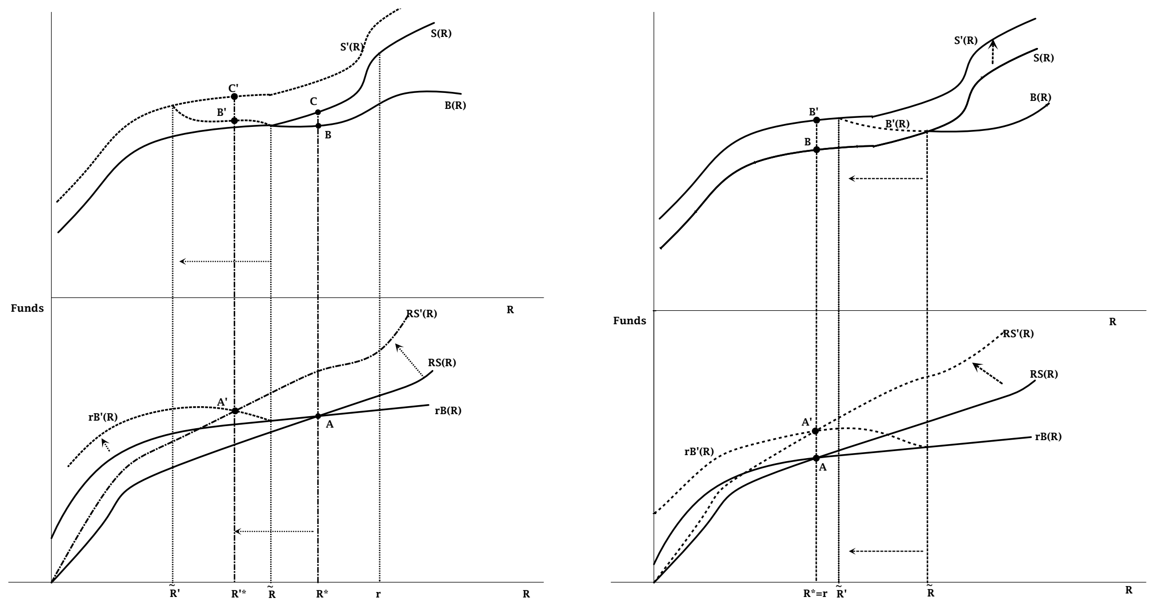
The above corollary considers only shifts in aggregate savings by the same factor in every period. We discuss later the fact that the time-profile of savings has an impact on the availability of funds for the group members. In particular, we will argue that shifting savings from later periods to earlier periods is always welfare improving to the group; while the opposite is welfare decreasing (see Remark 2). Hence, the above corollary is true also when early savings increases more than later savings (in percentage terms), but may not hold if later savings increase less than early savings.

The two corollaries illustrate one of the main results of the model: that exogenously increasing the funds available to the group (for example, by replacing one of the members of the group) will impose an externality on other participants. The key determinant of the sign of this externality is whether the group is resource constrained. Quite intuitively,

FIGURE 23. **Exogenous shift in aggregate savings:** In both cases, the initial equilibrium is determined by point A. Increasing savings to $S'(R)$ shifts the borrowing curve to $B'(R)$ (dotted line) for values of $R < \tilde{R}$ (i.e. when there is rationing).

(a) **Initially non-binding resource constraint.** R^* drops to $R^{'*}$. Savings increase from C to C', and loans increase from B to B'.

(b) **Initially binding resource constraint.** The new equilibrium remains rationed, R is unchanged and loans increase to B'.



when the resources within the group are scarce, adding more resources is beneficial to the others. More interestingly, when the group is not resources constrained, adding resources to the group hurts the group by decreasing the return on savings. These effects are demonstrated graphically in figure 23, which show the effect of a shift in the aggregate savings function assuming that $k = 1$, and that both $S(R)$ and $B(R)$ are continuous functions. The figure shows that loanable funds increase without affecting returns if borrowing remains rationed, but returns fall when funds are not rationed.

When the resource constraint is binding only in some periods, the overall welfare effect of adding resources to the group is ambiguous. All members are made worse off by the addition of extra funds because they decrease $R^\star$. However, net borrowers who are rationed out benefit from the availability of extra funds.

Increase in Aggregate Borrowing We can similarly analyze what happen when the group composition changes in a way that shifts $B_t(R)$ up in every period, leaving unchanged the aggregate supply of funds $S_t(R)$. This would be the case if, for example, a net saver is replaced with a net borrower who saves the same amount in every period, but uses these savings to actually borrow funds from the group.

If the aggregate resource constraint is never binding, by proposition 1, the effect of an increase in aggregate borrowing is an increase in $R^\star$, leading to the following corollaries (which we illustrate in Figure 24 for the case $k = 1$).

Corollary 3. *If the aggregate resource constraint is never binding, then an increase in $\sum_t B_t(R)$ leads to an increase in $R^\star$, higher individual savings and borrowing. Everybody in the group is better off.*

If instead the aggregate resource constraint is always binding, then the impact of an increase in aggregate borrowings depends on how the funds are rationed among borrowers. For example, if the new demand for funds goes completely unmet, then the existing member of the group are indifferent to the increase in the demand for funds. If instead the addition of a borrower decreases the amount of funds available to the other borrowers, then the existing borrowers are made worse off by the increase in the demand for funds.

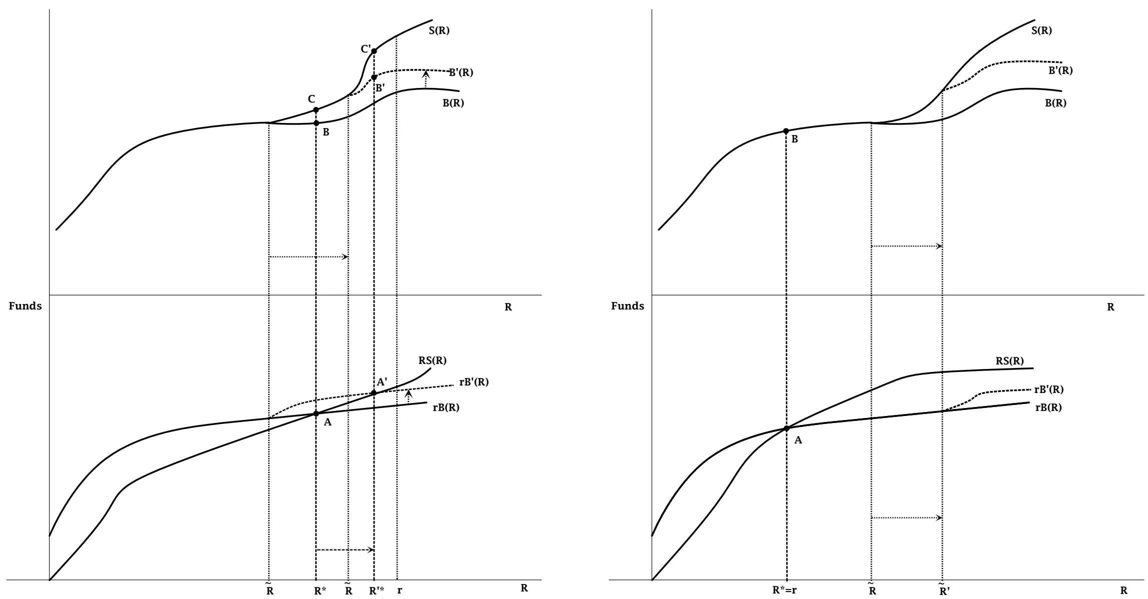
Corollary 4. *If the resource constraint is always binding, an increase in the demand for loans has no effect on $R^\star$, but may make rationing worse for some group members. As a consequence, everybody in the group is weakly worse off.*

Similarly, if the resource constraint is binding in some periods but not the others, the welfare effect of increasing the demand for funds is ambiguous. On the one hand, $R^\star$ increases and everybody benefits. On the other hand, net borrowers may be hurt by the fact that rationing is now worse.

FIGURE 24. **Shift in the demand for loans:** In both cases, the initial equilibrium is determined by point A. Increasing demand for loans shifts the borrowing curve to $B'(R)$ (dotted line) for values of $R > \tilde{R}$ (i.e. when there is no scarcity).

(a) **Initially non-binding resource constraint.** The new equilibrium is the intersection point A'. R^* increases to R'^*. Realized savings increase from C to C', and realized loans increase from B to B'.

(b) **Initially binding resource constraint.** The group remains rationed. R, realized savings and realized loans are unchanged.



Overall, increasing aggregate borrowing and increasing savings have opposite effects on the group. When the aggregate resource constraint is binding, increasing savings makes the group better off while increasing borrowing makes the group (weakly) worse off. When the aggregate resource constraint is not binding, increasing savings makes the group worse off, while increasing borrowing makes the group better off.

Supply of Funds Over Time There is an additional dimension that is relevant in determining the efficiency of the group: the timing of saving. Suppose that cumulative aggregate savings are constant, but the group can substitute one or more members, so that the timing of savings changes. In particular, assume that the reallocation leads to saving earlier. It is quite immediate to see that if the aggregate resource constraint is never binding, this reallocation of savings has no impact on the return on savings and no impact on the group members' welfare.

Instead, suppose that the aggregate resource constraints is binding in a given period $t < k - 1$, and savings are reallocated from period $t + 1$ to period t. If the period-t demand for loans is rationed, then this reallocation increases the loans given out in period t. In addition, all these loans will be repaid at the end of period t. So, for every dollar that is reallocated from period $t + 1$ to period t, $1 + r$ dollars become available in period $t + 1$. Hence, if the resource constraint is binding also in period $t + 1$, this reallocation eases rationing in period $t + 1$ as well.

Remark 2. *Suppose the resource constraint is binding in period t¡k-1. Suppose that $S_t(R)$ increases and $S_{t+1}(R)$ decreases by the same amount. It follows that $R^\star$ increases, and all agents increase their level of borrowing and savings. All agents are better off. If instead the resource constraint in period t is not binding, reallocating funds from one period to the other has no impact on $R^\star$ and no impact on the group members' welfare.*

Hence, contrary to changing the level of savings, changing the timing of savings has a unambiguous welfare effect.

Period 0: Setting the Rules

So far, we have treated the price of a loan r and the maximum savings $\bar{s}$ as given. In reality, these values are chosen by the group at the beginning of the cycle, possibly through voting. Might an optimal selection of these values eliminate the mismatch of demand and supply?

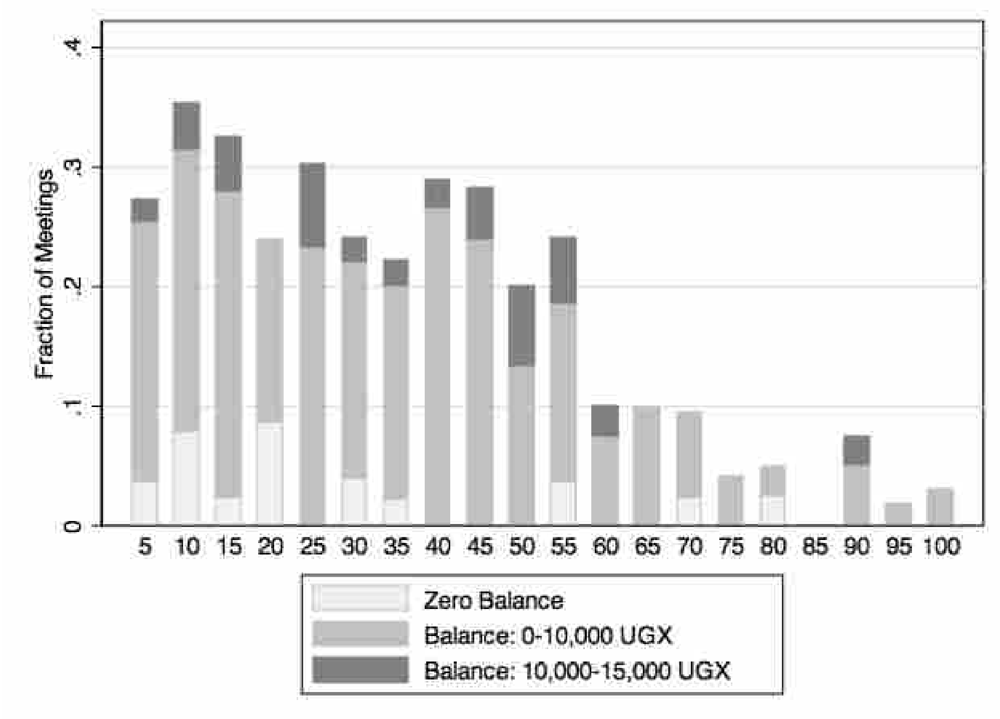
In short, the answer is "no". In Appendix B we argue that the payoff at share out is far in the future relative to the moment in which the choice of r and $\bar{s}$ are made, and hence plays a small role in deciding over r and $\overline{s}$. If we consider the limit case in which this payoff is completely disregarded by the the group members, then we can analyze the group's choice over r and $\overline{s}$ as a voting game and a Condorcet winner exists. The important observation is that, in general, when funds are scarce, some members may still be able to satisfy their demand for loans. Hence, the groups will choose rules that induce scarcity of funds, provided that the "median" member of the group is able to satisfy its demand for funds at these rules.

Evidence

The main takeaway from the theoretical model is that, in any given period, the demand for loans may not match its supply, and therefore groups are either operating under rationing or generating low return on savings. Whether and to what degree groups operate under scarcity or excess funds is thus an important issue, which we explore in this section.

Here, we use information from the cashbooks of 22 savings groups. For each meeting, the records include loan repayments, deposits and collected fines as inflows, loan disbursement as outflows, and a running balance of the cash remaining in the box (See appendix A for further discussion of the data). We begin by studying the amount of funds available in savings groups at the end of each meeting. Figure 25 shows the proportion of meetings in any meeting quantile that ended with a low balance. 20 to 35 percent of groups had less than 15,000 UGX ($5.60) available at the end of the day during the first half of the cycle. This proportion drops to less than 10 percent during the rest of the cycle. The graph is suggestive that groups may be operating under scarcity. However, it is possible that groups largely satisfy loan demand even if occasionally the box is empty. It

FIGURE 25. Fraction of Groups with Low Balances by Meeting Quantile



is also possible that groups that have cash on hand may still be rationing loans if potential borrowers need loan amounts that surpass the group balance.

An alternative strategy is to use the variation of inflows and outflows *within* the group in a regression setting. As we argue in the theoretical section, if groups are indeed resource constrained at any given meeting, the relationship between cash brought in (savings, repayments, and fines) and the amount lent out is close to one-to-one (see equation 4.7). That is, every dollar put in the box at the beginning of the meeting is lent out in the same meeting. This number can easily surpass one in magnitude if there are residual resources from previous meetings that are lent out. Groups are not resource constrained, on the other hand, if the amount of loans disbursed does not depend on the cash put into the box that day.

In order to identify whether groups are resource constrained across a lending cycle, we regress loans made at a particular meeting t in group g on the cash added to the box controlling for the cost of borrowing (captured by a group fixed effect). To allow for the relationship to change across time, we interact this cash-in measure with a series of dummy variables for the quantile of the meeting.[15] Equation (4.8) is our base specification:

$$L_{gt} = \beta_0 + \beta_1 CashIn_{gt} + \sum_{q=2}^{Q} (\beta_q CashIn_{gt} * D_t^q) + \sum_{q=1}^{Q} D_t^q + \alpha_g + u_{gt}, \tag{4.8}$$

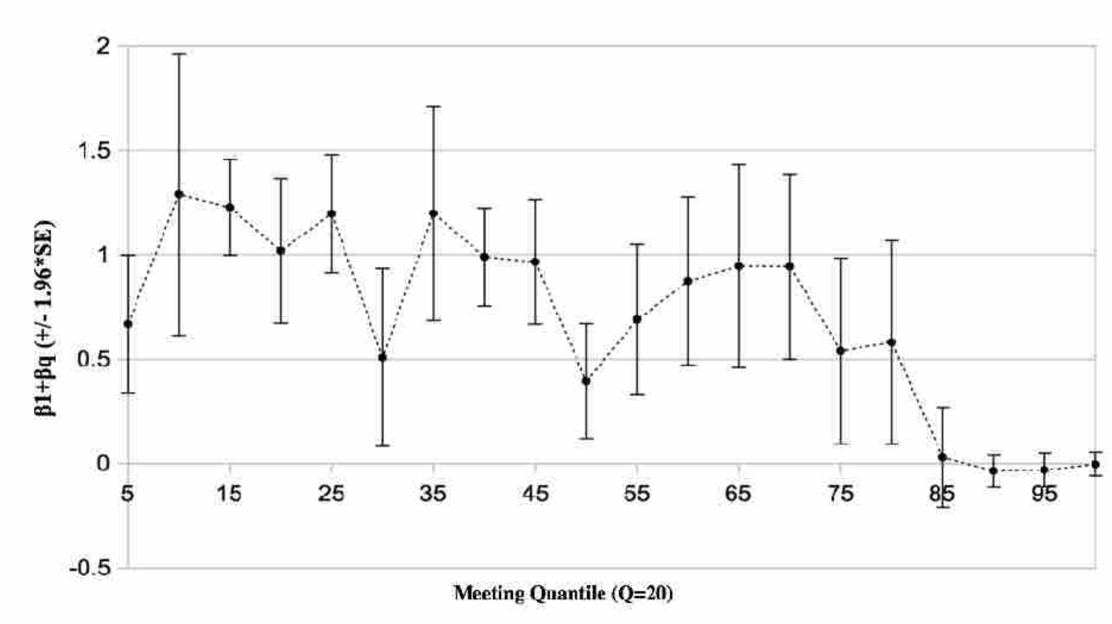
where L_{gt} are loans disbursed in group g during meeting t, $CashIn_{gt}$ are savings, fines, and loan repayments collected during that meeting, D^q is a dummy variable that takes on a value of one if the meeting falls in quantile q and zero otherwise, α captures group fixed effects (which controls for groups' characteristics and group's rules, including the cost of borrowing), and u_{gt} is an error term.

By including dummy variables in this way, we can interpret β_1 to be the fraction of cash brought in that was distributed out in loans during the first five percent of meetings, and $\beta_1 + \beta_q$ for $(q = 2, ..., Q)$ is the fraction of cash inflows that is lent out in each subsequent quantile. Periods where $\beta_1 + \beta_q = 1$ correspond to periods where all cash inflows are lent out, which suggests that loans are being rationed and limited by the availability of funds. Periods where lending is not constrained should be characterized by saving and borrowing being uncorrelated: $\beta_1 + \beta_q = 0$.

Figure 26 reports the parameter estimates $(\beta_1 + \beta_q)$ across twenty meeting quantiles. Initially, the group does not lend out all the cash brought in, possibly because each

[15]Meeting quantiles were used because groups varied in the total number of meetings held. Twenty quantiles were chosen, so the first quantile corresponds to the first 5% , the second quantile corresponds to the second 5%, and so on.

FIGURE 26. Estimate of β_q Over the Cycle



member needs to save with the group before being able to borrow. By the second quantile of meeting (10%) they appear to be lending at a nearly one-to-one rate with cash coming in, and that rate remains high for the first half of the cycle. Occasionally this estimate exceeds one, suggesting that residual balances may be compiling early in the cycle. Twice during the cycle, groups appear to loan only a fraction of the cash brought in during those meetings (at 30 and 50 percent of meetings). This may indicate a desire to accumulate funds for future lending of large loans. By three quarters of the meetings completed, groups are beginning to lend less (many stop lending all together) and cash brought in no longer affects lending decisions. Lending is shut down at the end of the cycle to allow repayment, and loans and cash in become uncorrelated.

Regression estimates for this figure can be found in Table 23. The first column of this table reports the OLS estimate for the average fraction of cash brought in that is distributed as loans across the cycle (controlling for group level difference in lending behavior). Because at the end of the cycle groups end lending altogether, this estimate is averaging over a series of zeros and we can anticipate that it may be biased downward. To accomodate for changes across the cycle, we interact the flow of cash in during a meeting with a dummy variable for the percentage of meetings that has passed.

Column (2) presents these results and are the basis for Figure 26. The first five percent of meetings are held as the base, so the parameter estimate for "Meeting Cash In" is the fraction of cash during the first five percent of meetings that was lent out. The following estimates report the difference in lending behavior from those first meetings. We find that during the first half of meetings, the fraction of cash brought in that is lent out increases compared to the first five percent of meetings. One exception to this is at the 30% meeting quantile where there appears to be a pause in the relationship.

This fluctuation between resource constraints and brief moments where groups have excess cash may be indicative of periods of savings, potentially for large loan amounts in subsequent meetings. As shown in Figure 1, loans do grow more frequent during the latter part of the cycle, so this sort of time rationing is plausible.

Robustness One potential concern that arises from this specification is that there may be an omitted variable influencing contemporaneous cash brought in during a meeting (savings, repayments and fines) and loans disbursed during that meeting. In particular, repayments on past loans are going to depend on the stock of outstanding loans in a particular period. Because each member can have only one outstanding loan at the time, groups with a larger stock of outstanding loans may have a higher cash-in and a lower demand for loans. Column (3) of Table 23 includes an interaction term for outstanding balance with the meeting quantile but the results do not appear to be sensitive to his change (the magnitudes and linear combinations are robust).

Seasonality may also affect how groups decide to loan out cash. This is a concern if the majority of the groups have meetings in roughly the same time of the year, and

TABLE 23. Lending of Available Resources Over the Cycle

	Dependent Variable = Cash Out in Loans			
	(1)	(2)	(3)	(4)
Meeting Cash In	0.393***	0.667***	0.631*	0.726***
	(0.0867)	(0.169)	(0.339)	(0.180)
Cash In*Meeting Quantile:				
10%		0.621*	0.626	0.712**
		(0.335)	(0.444)	(0.339)
15%		0.559***	0.615*	0.516***
		(0.172)	(0.361)	(0.186)
20%		0.351*	0.305	0.289
		(0.192)	(0.429)	(0.184)
25%		0.529***	0.730*	0.475**
		(0.190)	(0.373)	(0.206)
30%		-0.159	-0.0507	-0.248
		(0.239)	(0.427)	(0.240)
35%		0.531*	0.716	0.339
		(0.286)	(0.543)	(0.302)
40%		0.322*	0.412	0.240
		(0.193)	(0.366)	(0.203)
45%		0.298	0.363	0.220
		(0.213)	(0.364)	(0.234)
50%		-0.272	-0.316	-0.371*
		(0.200)	(0.348)	(0.215)
55%		0.0216	-0.192	-0.0532
		(0.260)	(0.395)	(0.278)
60%		0.207	0.267	0.148
		(0.248)	(0.406)	(0.256)
65%		0.277	0.631	0.196
		(0.273)	(0.451)	(0.289)
70%		0.275	0.515	0.230
		(0.272)	(0.417)	(0.278)
75%		-0.128	-0.192	-0.181
		(0.270)	(0.397)	(0.283)
80%		-0.0870	-0.0110	-0.133
		(0.285)	(0.404)	(0.294)
85%		-0.638***	-0.337	-0.681***
		(0.198)	(0.382)	(0.207)
90%		-0.702***	-0.628*	-0.759***
		(0.161)	(0.332)	(0.179)
95%		-0.698***	-0.672**	-0.757***
		(0.162)	(0.327)	(0.178)
100%		-0.670***	-0.637*	-0.731***
		(0.173)	(0.341)	(0.184)
Outstanding Loan Balance			-0.000434	
			(0.246)	
Constant	3,741	-32,837	-35,790	-46,991
	(30,187)	(22,929)	(27,247)	(40,002)
Observations	782	764	764	764
R-squared	0.331	0.476	0.525	0.481
VSLA FE	X	X	X	X
Meeting Quantile FE		X	X	X
Outstanding Balance*Meeting Quantile			X	
Month FE				X

Robust standard errors in parentheses

**** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$*

if groups face increased demand for loans at similar times (perhaps tied to agricultural planting and harvesting needs). In this setting, groups started the cycle at different periods of time. Moreover, to account for potential seasonality, we include dummy variables for month of meeting and report the estimated in Column (4). In general, the results from estimating Equation (4.8) do not change drastically with this adjustment.

Conclusion

In this paper we provided a theoretical framework for the analysis of supply and demand for loans within savings groups. The main result from the theory is that there is no mechanism to ensure that demand and supply of funds are in equilibrium, and that consequently groups either face excess supply of funds or rationing of loans. In this context, shocks to individual demand or supply curves create a spillover effect: they affect the availability of funds to rationed borrowers, or the return of savings.

**** We use the model to perform some comparative statics analyses. Most notably, we find that shifting savings from late to early in the cycle is always Pareto improving, because it eases scarcity in periods when the demand for loans exceeds the supply for loans without reducing the return on savings. Furthermore our empirical analysis shows that groups face binding resource constraints in the first part of the operating cycle. Hence, overall, the paper points at the importance of encouraging early savings.

From a policy perspective, encouraging early savings may be achieved by adjusting the rules of operation of savings groups. For example, decreasing the number of shares that can be purchased (starting from a relatively large number) could successfully shift savings from later periods to early periods. Alternatively, early savings could earn a higher return than later savings. For example, shares could be sold at a discount during the initial period of operation of the group, under the condition that each share receives the same payout at share-out. Finally, programs that temporarily fund savings groups early in a cycle through a microfinance loan may also encourage early lending without necessarily hurting savings returns.

CHAPTER V

CONCLUSION

This dissertation examines three major economic issues facing developed and developing countries today: substance abuse, criminality, and financial inclusion. I present two papers which explore the impact of a novel policy and question the assumptions made about determinants of risky behavior in the United States. I also include one paper focusing on policies designed to improve welfare of individuals in developing nations.

Chapter II contributes to our understanding of the impact of state-wide health insurance reform on substance abuse and overdose. Legislators began passing laws requiring insurers to cover rehabilitation and detoxification treatments in insurance plans as a way to mitigate the growing concern over substance abuse in the United States. I show that these laws have a measurable impact on the uptake of services but that they are limited in the ability to reach groups struggling with certain types of addiction, notably addiction to opiates. Moreover, I illustrate that coverage of substance abuse treatment is not necessarily having a significant impact on the overdose death rate. This has several major implications. First, in absence of legislation expanding insurance to risky populations, populations most at risk for overdose are less affected by the law. Secondly, did have large amounts of uptake suggesting affected populations have unmet demand for services.

In Chapter III, provides several factors to our understanding of the determinants of criminality. Previous literature has found a consistent positive relationship between unemployment and property crime rates and no relationship with violent crime rates. Appealing to the seminal paper by Becker (2000), I provide reason to suspect time-variation in these relationships and explore whether this has occurred using estimated confidence intervals and dummy variable techniques. The results suggest that crime rates are no longer positively correlated with unemployment in recent years. Additionally, there is evidence that some measures of violent crime are negatively related to unemployment rate during the last decade. This upends our current understanding of this determinant of crime and creates a need for further investigation on the subject.

In my last substantive chapter, I present a coauthored investigation where we contribute novel theory on the functioning of savings groups, an increasingly popular type of informal financial institution. A main conclusion from this theory is that groups are likely to operate under scarcity of funds or have surplus of savings that are not distributed as loans. Using administrative data from a set of newly formed Ugandan savings groups, we text these predictions and find that groups are typically rationing available funds, which indicates that there are welfare improving changes to group formation and operation that can be made. However, we also find that despite rationing, savings groups are able to generate high returns to savings.

The results from the papers included in this dissertation fit within a general research agenda focusing on policies design to improve the welfare of at risk populations domestic and abroad. Risky behaviors such as drug abuse, suicide, and crime are continuing problems world-wide and continued investigation on the impact and determinants of these issues is necessary.

APPENDIX A

LEDGER DATA CLEANING

The paper made use of meeting-level data from handwritten registries of a number of Ugandan savings groups (see Table 24). Of the 110 groups that were part of the study, 70 groups submitted photographs of their cashbooks for their first cycle. Many of these pictures had missing pages, poor focus, or were otherwise difficult (if not impossible) to digitize. We found that 29 groups had substantial portions of their cashbooks missing or were in formats that were illegible. Of the remaining 41 groups, 22 were thoroughly cleaned and reconciled.

TABLE 24. Description of Cashbook Cleaning Process.

Total groups with any cashbook records	70
Number of groups dropped due to incomplete records	29
Number of groups with complete cashbook records (unvetted)	19
Number of groups with complete cashbook records (vetted)	22
Total number of observations	944
Percent of observations corrected*	59.2
	(49.169)
Percent of observations with residual discrepancy	44.068
	(49.673)
Average size of discrepancy (in absolute value, UGX)	43541.450
	(226170)

Standard deviation in parentheses

* Corrections include: missing data from data entry (frequent), typos in data entry (frequent), miscalculations of record keeper (rare), and differences in accounting procedure (moderate frequency).

In order to determine whether there was an error in any particular record, we reconstructed the cash-in-the-box balance from meeting to meeting (cash-in minus cash-out plus balance from previous period). We then looked at the difference between the reported balance with our calculated balance and found that 59.2% of the observations required an edit. The primary reason for these edits were omissions and typos due to the digitization of the picture data which was easily corrected for by looking at the photos and inputting the correct amounts. Occasionally, there was a miscalculation or written error by the record keeper for the group which could be correctly interpolated from correct data. Even through our careful cleaning, 44.1% of observations retained some level of discrepancy (but we minimized this amount as much as possible). On average the size of this discrepancy was about 972 UGX, but the range of this amount was quite substantial.[1]

[1] A lot of these discrepancies occurred on observations in the middle of the cycle which were corrected for by audits throughout and there was fewer discrepancies during the latter parts of the cycle.

APPENDIX B

THEORETICAL EXTENSIONS

More on Rationing

It is interesting to note that, if we allow some convexities in the outside investment, the uniform rule may fail to be either efficient or resource monotonic. For example, suppose that all investment opportunities are discrete, in the sense that they require a fixed investment level to deliver a given return. It follows that an agent's utility may have local maxima, which emerge whenever extra funds allocated to the agent are not sufficient to start a new investment opportunity, but need nonetheless to be repaid with interest. When resources are scarce, an agent may borrow little and settle for a local maximum. As aggregate resources increase, some agents may discretely increase the amount borrowed with the group, potentially decreasing the resources available to other members of the group.

Motivated by this observation, we consider here a second widely-studied rationing rule: *serial dictatorship*, in which all agents are ordered and each of them can, in turn, choose how much to receive from the available funds. Serial dictatorship is appealing because it is efficient, strategy proof and satisfies resources monotonicity whenever two conditions are met:

- when indifferent between multiple borrowing levels, members demand the lowest level.
- consider the list of dictators, $1, 2, ...k$, where dictator 1 chooses before all other dictators (and so on). If the k^{th} dictator borrows a positive amount, then all $k-1$

dictators fully meet their demand for loans. i.e. they would not borrow more even if more resources were available.

To understand better the last point, suppose that an earlier dictator leaves funds to the following dictator, who then uses these funds. The above condition rules out situations in which an earlier dictator can only invest in projects requiring an upfront investment larger than the available funds (and therefore leaves funds on the table), while the later dictator can invest in projects that require an upfront investment lower than the available funds. This condition is always satisfied if the return on investment is continuous, smooth and concave. It is also satisfied if all investment opportunities faced by all agents have the same minimum investment level (but may deliver different returns).

Hence, the uniform rule has very appealing properties if all $f_i()$ are smooth and concave, but it fails to be resource monotonic in other cases. Serial dictatorship has less appealing properties (in particular, it does not satisfy the no-envy condition), but remains efficient, strategy proof and resource monotonic also for some $f_i()$ that are not convex.

Rules Setting

In period 0, the choice of r and $\overline{s}$ is determined by two basic trade-offs. For given $R^\star$ and given available funds, a higher r or a lower $\overline{s}$ will make everybody in the group weakly worse off. However, a higher r or a lower $\overline{s}$ may actually increase $R^\star$, benefiting everybody in the group. Furthermore, r and $\overline{s}$ have an additional effect on the availability of funds and on whether some borrowers will be rationed out. Crucially, each group member will solve these trade offs differently depending on their demand for funds and on the rationing mechanism.

For this reason a voting game over the rules $r, \overline{s}$ may not have a Condorcet winner. A group member may have a preferred r and $\overline{s}$ in case she is a borrower and a preferred

r and $\overline{s}$ in case she is a pure saver (i.e. no borrowing). If a borrower, an agent is facing a trade off between availability of funds (which is increasing in r), and cost of borrowing. In general, an agent prefers the smallest r such that her demand for loans is fully met to any larger r (but may, in fact, prefer an even smaller one). If a pure saver, the agent prefers the r and $\overline{s}$ that maximize $R^{\star}$. Hence, an agent's utility may be first decreasing and then increasing with r if the agent switches between being a borrower to being a saver.

When preferences are not single peaked, the collective decision over r and $\overline{s}$ depends on the details of the voting game being played, such as who can propose options for voting, how many voting rounds are allowed, how long can voting last, whether options that have previously been outvoted can be re-proposed, and so on. Because the voting procedure is not part of the model, each group is likely to have adopted a different voting game. Despite these difficulties, we can show that, under some strong assumptions, the voting game has a Condorcet winner. We assume here a uniform rule for allocating scarce funds.

Proposition 2. *Suppose that $\beta_i = 0$ for all i, so that, in period 0, each group member maximizes $u_1(c_{i,1})$. Call $r_i^{\star}$ the preferred r of agent i (if it exists). There exists a Condorcet winner of the game, which is the median $r_i^{\star}$ (which we call $r_m^{\star}$) and the $\overline{s}$ maximizing the availability of funds for this r.*

It is reasonable to assume that, in period 0, all members of the group discount heavily the payoff at share out relatively to the instantaneous payoffs earned while the group is operating, because the share-out date is sufficiently far in the future while the date at which each agent may borrow from the group is much closer. The proposition considers the limit case $\beta_i = 0$ for all i, in which the utility at share out is completely ignored and the only determinant of the choice over r and $\overline{s}$ is the ability to borrow cheaply in period 1. Hence, for every r, everybody agrees that $\overline{s}$ should maximize the availability of funds.[1] When choosing over r, conditioned on the agent being a borrower, preferences are single peaked, because a higher r reduces rationing but makes borrowing more expensive. In case an agent does not expect to borrow, she will be indifferent over r and $\overline{s}$. A Condorcet winner exists if agents break their indifference in favor of the option closer to their peak.

Finally, some agents are never borrowers and therefore do not have a peak r. The Condorcet winner is the median peak if these agents abstain. However, other Condorcet winners may exists, depending on the number of agents who never borrow and on how these agents break their indifference. For example, of only one agent in the group is always a saver, there are two other Condorcet winners. Assuming that the agent who is always a saver always votes for the largest r, then the peak just above the median peak is a Condorcet winner. Similarly, assuming that the agent who is always a saver always votes for the smallest r, then the peak just below the median peak is a Condorcet winner.

Despite being based on fairly strong assumptions, the above proposition is relevant because it shows that the outcome of the voting game will, in general, not reflect the "preferences" or "welfare" of the group, but rather the preferences of the median member of the group. In particular, note that if $r_i^\star > r_m^\star$ for at least one i, then the interest rate chosen by the group will generate rationing, because some of the group's member will not be able to borrow as much as they want at the chosen $r_m^\star$.

[1] Note the amount of cash available for borrowing may not be monotonic in $\overline{s}$. For example, if the person saving the most is actually a net borrower, constraining this person in the amount she can save may generate more resources to the remaining members of the group.

APPENDIX C

MATHEMATICAL DERIVATIONS

Proof of Lemma 1

Proof. Because the objective function of the utility maximization problem is quasiconcave, and all constraints are continuous and convex valued, by the theorem of the maximum $s_{i,t}(r, R, \tilde{C}_{i,t})$ and $b_{i,t}(r, R, \tilde{C}_{i,t})$ are upper hemicontinuous, closed and convex for all r, R and $\tilde{C}_{i,t}$. In addition, note that $s_{i,t}$ and R are complements in the objective function. Therefore by Topkins's theorem $s_{i,t}(r, R, \tilde{C}_{i,t})$ is weakly increasing in R (if $s_{i,t}(r, R, \tilde{C}_{i,t})$ is a correspondence, then lower and upper bound of this correspondence are weakly increasing in R).

Finally, $b_{i,t}(r, R, \tilde{C}_{i,t})$ is weakly increasing in $\tilde{C}_{i,t}$ because increasing $\tilde{C}_{,t}i$ relaxes the aggregate resource constraint and allows for higher borrowing. At the same time, because of Equation 4.1, an agent may save to borrow. When the resource constraint is binding, $b_{i,t}(r, R, \tilde{C}_{i,t}) = C_{i,t}$. Hence, as $C_{i,t}$ increases, the amount that can be borrowed increases, and with it the amount that may need to be saved in order to reach a given level of borrowing. □

Proof or Proposition 1

Proof. Note that the aggregate demand for savings and aggregate demand for loans inherit the properties of the individual demand for savings and loans derived in Lemma 1 and remark 1. Note also that each $S_t(R)$ is bounded above by $\sum_i \min_i\{w_i, \overline{s}\}$. It follows that each $B_t(R)$ is also bounded above. Hence, for R sufficiently large:

$$R \sum_t S_t(R) > r \sum_t B_t(R)$$

At $R = 0$ members are indifferent between saving inside or outside of the group. Whenever savings inside of the group are positive, also borrowings can be positive and $r \sum_t B_t(R) \geq 0$.

Hence, it must be the case that

$$R\sum_t S_t(R)|_{R=0} = 0 \leq r\sum_t B_t(R)|_{R=0}$$

Together with the fact that all functions are upper hemicontinuous and compact valued, these results imply that an equilibrium exists.

Finally, as β_i decreases, each $B_t(R)$ becomes progressively flat, because the borrower's behavior becomes independent on R (and depends exclusively on r). At the same time, by Lemma 1 $S_t(R)$ is always (weakly) increasing. Therefore, as β_i decreases for all i, $r\sum_t B_t(R)$ becomes flat, while $R\sum_t S_t(R)$ is strictly increasing and diverges to infinity. It follows that the equilibrium must be unique. It also follows that at the unique equilibrium $R\sum_t S_t(R)$ must cross $r\sum_t B_t(R)$ from below. □

Proof of Corollary 2

Proof. If all aggregate resource constraints are binding, then at $R = R^{\star}$:

$$R\sum_t^k S_t(R) = r\sum_t^k S_t(R)\sum_s^{k-t}(1+r)^s$$

Which implies that increasing all $S_t(R)$ by the same factor does not change $R^{\star}$. At the same time, higher $S_t(R)$ relax the aggregate resource constraint. Net savers and borrowers who are not rationed out are indifferent, while borrowers who are rationed out increase their borrowing and are better off. □

Proof of Proposition 2

Proof. We start by making few preliminary observations. First, the availability of funds within the group is increasing in r. An increase in r causes three responses. Those who did not borrow at all do not change their behavior. Some of the borrowers will decrease the amount borrowed, but continue borrowing. Finally, some of the borrowers will switch from being borrowers to being savers. It follows that increasing r always (weakly) increases the availability of funds to those who remain borrowers. Second, because the individual demands and supplies of funds are are upper hemicontinuous in r (by the theorem of the maximum), also the funds available for borrowing are upper hemicontinuous in r. Third, for r sufficiently large, nobody will want to borrow and, quite trivially, the demand for loans of the entire group is satisfied.

For every agent i, call $r_i^\star$ this agent's preferred r, which is computed solving for the trade off between borrowing cheaply and being able to access funds. Note that this $r_i^\star$ may not exist for all group members, but will exist for some member as long as $f'_{i,1}(0) > 0$ for some i. The reason is that, by the uniform rule, as long as the group has some funds to distribute (i.e. as long as there is one saver in the group), then everybody who demands funds will receive some. On the other hand, if the agent expects to be a saver for every r, then $r_i^\star$ does not exist because this agent is indifferent among all r.

If $r' > r_i^\star$, $r'' > r_i^\star$, $r' > r''$, and assuming that the agent is a borrower at r'', the agent prefers r'' to r', because conditionally on being able to meet his demand for loans, this agent strictly prefers lower r. Similarly, if $r' < r_i^\star$, $r'' < r_i^\star$, $r' > r''$, and assuming that the agent can borrow a positive amount at r', this agent prefers r' to r'', because this agent will be able to access more funds (remember that, by the uniform rule, more funds for the group imply more funds available for each member of the group). Furthermore, this agent always prefers an r at which she is a borrower to an r at which she is a saver, and is indifferent between all r for which she is a net saver.

Hence, preferences are single peaked over r (and a Condorcet winner exists) as long as we impose the following tie breaking rule: in case of indifference, an agent will vote for the option that is closer to her peak. Note, however, that agents who are always savers do not have a peak r. Depending on how these agents break their indifference, we may have different Condorcet winner. Here we assume here that, if indifferent among all options, these agents do not vote, so that the Condorcet winner is the median peak r. To conclude, note that every borrower prefers the $\overline{s}$ that generates more funds to any other $\overline{s}$, because it allows to maintain the same level of rationing but at lower r's.

$\square$

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