ESSAYS IN ENVIRONMENTAL ECONOMICS

by

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Title: Essays in Environmental Economics

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DISSERTATION ABSTRACT

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This dissertation focuses on two aspects of Environmental Economics that are critical in cost-benefit analysis. Chapters II and III focus on estimating potential costs of drought that may be exacerbated by climate change, and Chapter IV focuses on examining the hedonic property value model that is commonly used to estimate potential benefits of environmental regulation. In Chapter II I estimate the impact of drought on crime in South Africa. Using a police-station by year panel, I exploit variation in the timing of droughts and water management policies to explain changes in crime. I find that violent crimes increase by 10%, police-detected crimes fall by 20%, and that there is no discernible impact on sex crimes or property crimes. These findings suggest that in the future, especially as severe droughts become more prevalent due to climate change, crime prevention may be an important component of climate policy. In Chapter III I examine how exposure to drought affects migration in the United

States using a dataset of bilateral migration flows from 2000–2013. I find that moderate and severe drought do not significantly influence migration, but that exceptional drought and multi-year severe droughts reduce out-migration from afflicted counties. I further find that this result is strongest in low-income and high-poverty counties. These results suggest that adaptation to climate change through migration may be limited for disadvantaged groups in the United States. In Chapter IV I examine how the presence of a bubble in the housing markets affects estimates in a hedonic propery value model. The results indicate that the bubble does cause bias in the naive estimates, and that the extent of the bias increases with the size of the bubble.

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CHAPTER I

INTRODUCTION

The essays in this dissertation cover two broad topics. The first is the social effects of drought and water shortages. In this dissertation I explore two possible effects; increases in crime in the first substantive chapter and changes in migration in the second substantive chapter. The third substantive chapter explores the hedonic property value model, used to estimate the value of environmental amenities, and examines whether a bubble in the housing market could bias estimates recovered from this model.

The first substantive chapter uses station-level data from the South African Police Department in combination with precipitation data to create a station-year panel dataset. The crime data consist of annual counts of seventeen distinct types of community-reported crimes and three types of police-detected crimes. The precipitation data are measured monthly on a 0.5×0.5 lat/long grid. I aggregate the precipitation data to the police-station level by matching the four nearest grid points to the centroid of the police jurisdiction, and weighting the value by the inverse distance to the station.

I also use demographic data from the South African Census. These data are matched to the station jurisdiction boundaries using areal interpolation. I assume that the population of each census ward is distributed evenly over the area of the ward, and then calculate the area of the ward that belongs to each police station's jurisdiction. I then assign the population proportionally to this area.

I model the numbers of crimes at each station using a negative binomial regression with fixed effects at the station level as well as year fixed effects. I first estimate the impact of drought on crime in general. With less precipitation, I find a statistically significant increase in violent crimes, sex crimes, robberies, and police-detected crimes, but do not find a statistically significant change in property crimes.

I then test whether there is an additional effect of an indicator for severe drought beyond just the linear relationship with precipitation in general. Under severe drought conditions, I find significant increases in violent crimes and robberies and significant decreases in police-detected crimes. I do not find a statistically significant difference for sex crimes or property crimes.

Additionally, I examine whether the imposition of exceptionally stringent urban water-use rationing affects crime. I use an indicator variable for those jurisdictions in the greater Cape Town metropolitan area which were subject to stringent regulations on water use in 2018. While controlling for the general effects of drought, I find that these regulations increase both violent crimes and robberies, and reduce the detection of other crimes normally discovered by police.

I then explore whether these increases in crime are specific to certain types of locations. Using the demographic variables from the census, I find that the increases in crime are strongest in more affluent areas and in areas where a higher proportion of the population is white.

Collectively, these results suggest that drought and dry conditions lead to increases in some types of crimes, and that these increases can be exacerbated by severe drought and when stringent water rationing may be necessary to preserve the remaining water supply.

The second substantive chapter of this dissertation looks at the effects of drought on migration in the United States. This project uses data derived from

2000–2013 tax returns to obtain measures of county-to-county migration in the United States. I combine these migration data with measures of drought exposure at the county level from the United States Drought Monitor to estimate the effects of drought on migration.

I model the log of the number of migrations between each county pair using a fixed effects model to control for the factors that determine the number of migrations between each origin and destination county pair. I find that moderate and severe drought have little impact on migration in the U.S. However, I find that extreme drought in the origin county leads to a reduction in out-migration, suggesting that individuals in drought locations may be stuck in liquidity traps that reduce the number of migrations.

I then estimate the model using indicator variables for origin counties that are experiencing multi-year drought events. Counties whose populations are exposed to moderate through extreme drought for three or more years experience a reduction in out-migration of 2-3%. I further explore this result by subsampling based on demographic variables in the origin-county. I find that counties with higher poverty rates and lower median incomes see a stronger effect, but that counties with larger proportions of hispanic, black, or working age population do not. I also find that counties that are less urban or have a higher percentage of farms do not.

The third substantive chapter explores a different side of the environmental economics literature, the hedonic property value model. This model is widely used to estimate the value of environmental amenities such as clean air, as well as other public goods such as school quality. This chapter studies the potentially confounding effects of a bubble in the housing market. In general, bubbles cause housing prices to become artificially high, and this may cause the measured implicit price of an environmental amenity to be unreliable.

For this chapter, I use a Monte Carlo simulation to mimic a housing market under the presence of a housing bubble. Using simulation techniques allows me to have full information about the "fundamental" price of the house as well as the mark-up that is due to the presence of the bubble. Observational data do not allow for the separate, direct measurement of these two components. After simulation of a market equilibrium, I recover estimates of the marginal price of an environmental amenity and I find that the bubble does bias the estimates of the marginal price for that amenity, and that the size of this bias depends on the size of the bubble.

CHAPTER II

THE IMPACT OF DROUGHT ON CRIME IN SOUTH AFRICA

Introduction

Water is critical input to agriculture and industry as well as being a daily requirement for human life. Severe drought can reduce the available supply of water and induce competition for access to it. Competition for an essential but scarce resource can create conflict.

There is burgeoning evidence that drought and climate shocks may lead to conflict or violence, in low-income countries in particular. There is also evidence that heat and drought lead to increases in crime in high-income countries. It is unknown what impacts drought and climate change have in middle-income countries. The recent and severe South African drought provides a unique opportunity to study the effects of drought in a middle-income country. This uniqueness comes from the fact that while South Africa is a middle-income country, it has the highest inequality in the world.[1] Thus, South Africa provides a setting where we can study drought's effects for impoverished people and for their affluent neighbors.

In this paper, I study the impacts on crime of drought, water scarcity, and urban water-use rationing. I use crime data from the South African Police Service, drought data from the National Center for Atmospheric Research, and demographic data from StatsSA. I combine these three data sources to create a dataset on crime and drought conditions at the police-station level.

[1] http://povertydata.worldbank.org/poverty/region/SSF

I use a negative binomial model to show that a one standard-deviation reduction in precipitation results in a 1.4-2.7% increase in reports of violent crimes, sex crimes, robberies, and police-detected crimes, but does not cause a statistically significant change in property crimes. Severe drought causes a 3% additional increase in violent crimes, and a 14% *reduction* in police-detected crimes. Next, I estimate the effects of the strict water rationing implemented in 2018 in the greater Cape Town metropolitan area. This rationing is associated with a 4% increase in violent crime, an 8% increase in robberies and a 20% reduction in police-detected crimes. Increases in crime are largest in areas that have high average income, and have a higher proportion of white population.

A "back-of-the-envelope" calculation for the changes in crime suggest that the rationing resulted in an addition 335 murders, 502 car and 85 truck hijackings, 475 robberies at residence, as well as 4470 additional DUIs that went undetected.

Overall, the evidence points to a pattern in which drought affects violent types of crime, but does not affect non-violent property crimes. This is in line with a number of papers that have linked drought to conflict in developing countries (Reuveny, 2007; Burke et al., 2009; Hsiang et al., 2011; Fjelde and von Uexkull, 2012; Hendrix and Salehyan, 2012; Scheffran et al., 2012; Hodler and Raschky, 2014; Aidt and Leon, 2016; Almer et al., 2017), however, this is in stark contrast to evidence from the United States, where drought has been found to increase property crimes but not violent crimes (Goin et al., 2017).

These results will help policy-makers understand the full consequences of drought. As climate change progresses, drought is expected to become more prevalent, and to affect areas that have not previously been vulnerable. This paper suggests that it is important to allocate government and police resources during a drought to prevent crime escalation.

The paper proceeds as follows: Section 2 provides background on the link between drought and crime, and explains the South African context. Section 3 describes the data sources and outlines the model used to estimate the impact of drought on crime. Section 4 describes the results and a discussion of their implications. Section 5 concludes.

Background

Droughts, Crime, and Conflict

Droughts have a multifaceted effect on the natural environment and human welfare. Droughts directly reduce crop yields, accelerate forest loss, damage habitats for fish and wildlife, and harm livestock. These consequences can, indirectly, lead to reduced income for farmers, unemployment, increased crime, civil unrest to the point of war, and migration. These indirect losses can sometimes exceed the direct losses (Wilhite et al., 2007).

There is still a need for further study to determine the true extent of the potential social damages from climate shocks. This is particularly urgent in low income countries, which will be the most vulnerable to water shortages and droughts (Gleick and Heberger, 2014).

Drought has been linked to harmful effects on health, both directly through water scarcity, as well as through the income shocks in agricultural communities as explored by Burgess and Deschenes (2011); Kudamatsu et al. (2012); Burke et al. (2009); Dinkelman (2017). In other work, Raddatz (2009), Schlenker and Lobell (2010), Loayza et al. (2012), and Fomby et al. (2013) show that drought reduces long-run economic growth. Several papers also find significant short-run effects of drought. Both Fafchamps et al. (1998) and Kazianga and Udry (2006) show that rural Africans experience significant income losses, and Dell et al. (2014) find that livestock holdings do not provide rural Africans with sufficient insurance against drought-related losses.

Recently, several studies have demonstrated that drought, heat, and climate change are linked to conflict, rioting, and civil war (Reuveny, 2007; Burke et al., 2009; Hsiang et al., 2011; Fjelde and von Uexkull, 2012; Hendrix and Salehyan, 2012; Scheffran et al., 2012; Hodler and Raschky, 2014; Aidt and Leon, 2016; Almer et al., 2017). Miguel et al. (2004) link drought-induced income shocks to an increased risk of civil war in Africa. Some studies argue the association is not causal, and that climate and climate shocks are not the true cause of the conflicts (Buhaug, 2010; Ciccone, 2011). Salehyan (2014) reviews the competing viewpoints in this literature.

In developed countries, where institutions are stronger, conflict and rioting are less likely. However, competition for scarce water may drive increases in crime Butler and Kefford (2018). Becker (1968)'s rational crime framework suggests that droughts could increase crime via several mechanisms. Unemployment and income losses in the agricultural sector may reduce the opportunity cost of committing crimes. Severe resource scarcity may reduce the societal stigma associated with committing a crime. [2] Social conflict over reduced access to common-property resources, in general, may contribute to criminal behavior, a relationship explored

[2]With the drought in Cape Town, South Africa, for example, there is evidence that resentment against wealthy households has escalated because these households can afford to drill private wells to bypass regulations on water consumption. https://www.washingtonpost.com/news/world/wp/2018/02/23/feature/as-cape-towns-water-runs-out-the-rich-drill-wells-the-poor-worry-about-eating/?noredirect=on&utm_term=.fe75d80349c5

by Barnett and Adger (2007) and Agnew (2012). Under-priced urban water supplies may be one example of such a resource.

Crime will also increase if the risk of punishment is reduced during drought confditions. For instance, police personnel preoccupied with the enforcement of water rights, may be less likely to investigate and prosecute other types of crimes. Victims are less likely to report a crime if they believe the police will not devote resources to solving the crime. During a time of social conflict, perpetrators may believe that the risk of being caught and punished is lessened.

To date, however, there have been few studies that attempt to examine the specific research question posed in this paper—whether drought affects crime. Goin et al. (2017) consider the drought that affected California during 2011–2015. Using a synthetic control strategy, they estimate that property crimes increased approximately 9% but find no significant effect on violent crimes.

There is also a broad literature on how heat and weather affect crime (Lab and Hirschel, 1988; Field, 1992; Anderson, 2001; Simister and Cooper, 2005; Talaei et al., 2008; Butke and Sheridan, 2010; Horrocks and Menclova, 2011; Sorg and Taylor, 2011; Mares, 2013a,b; Ranson, 2014). The focus of these papers is mostly on short-term variation in weather or temperature, and they find that the number of crimes committed tends to increase when the weather is hot and when precipitation is low.

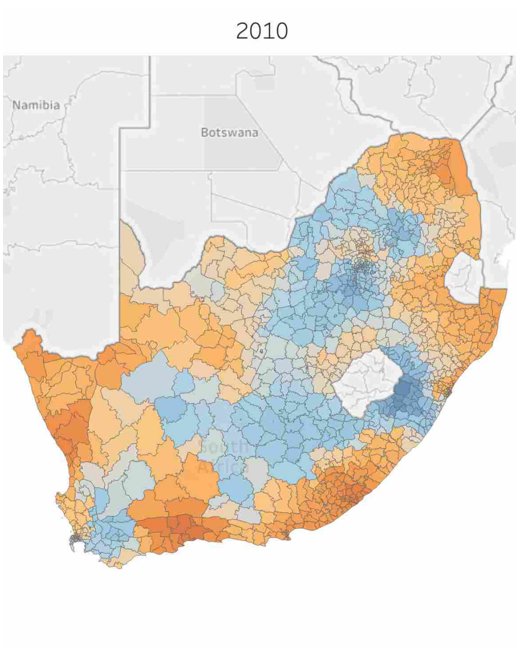
The 2015–2018 South African Drought

Cape Town, South Africa, began experiencing an increasingly severe drought in 2015. The initial drought in 2015 and 2016 affected most of the country, as can be seen in the maps of Figure 1. By 2017, the rest of the country returned to normal levels of rainfall, while Cape Town continued to experience meager levels of rainfall. The Western Cape Province that surrounds Cape Town constitutes a distinct climate zone. The majority of the country receives major rainfall during the summer months of the Southern Hemisphere (December–March) due to weather patterns that bring moisture south from the center of the continent. The Western Cape receives rainfall primarily during the winter months (June–September) with moisture that blows inland from the southwestern ocean. This meteorological difference has caused the drought experienced in the Western Cape to be both more sustained, and also more severe, while leaving the rest of the country relatively insulated from its effects.

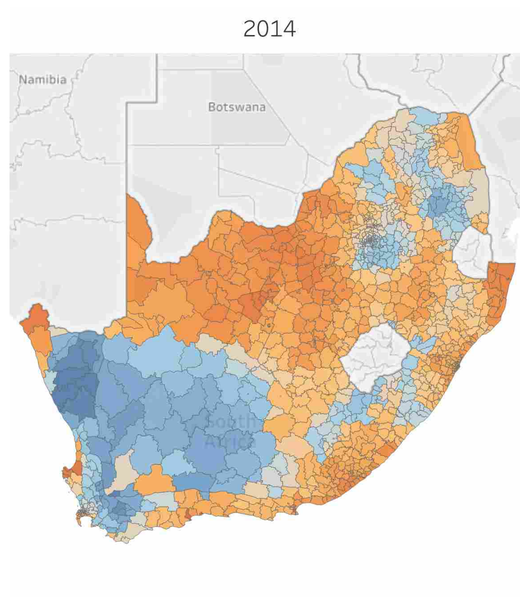
The greater Cape Town area draws its water from reservoirs created by six major dams. The time-series plot in Figure 2 shows the amount of water in storage. For the years 2008–2015, Cape Town used approximately 35% of the total dam capacity per year during the dry season, and this draw-down has been replenished in most years during the following rainy season. During the first year of the drought in 2015, Cape Town used extra water (slightly more than 50% of the capacity of these six reservoirs) to respond to the drought. Area farms had received low rainfall, so the local government supplied them with supplemental irrigation water from these reservoirs. When rain was again low in 2016, reservoir usage was similarly high. When rainfall in 2017 had still not returned to normal, the city began to ration the water to farmers and to implement urban water-use regulations. The rainy season of 2017 was historically low. With reservoirs holding water at only 25% of their capacity at the beginning of the dry season, and that strict regulations would be necessary to ensure that the reservoirs did not run dry.

FIGURE 1.
Drought Severity over Time

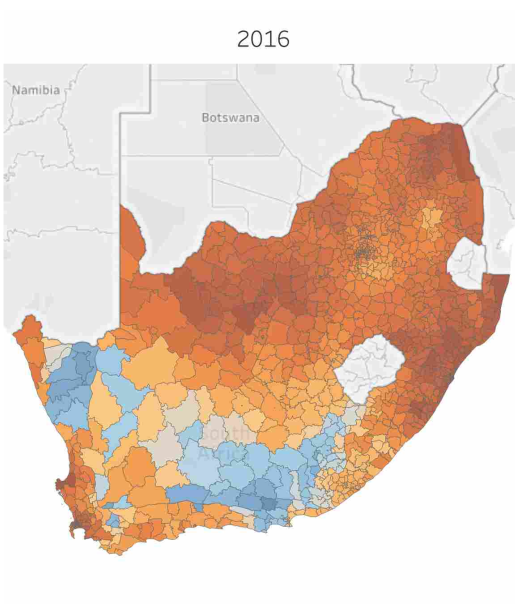
(a) 2010



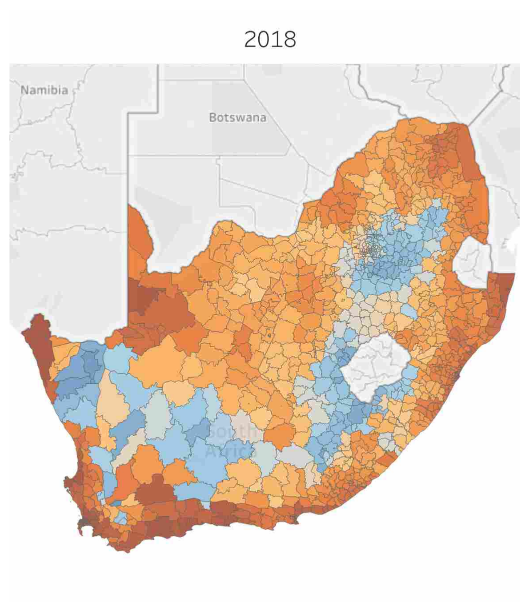
(b) 2014



(c) 2016

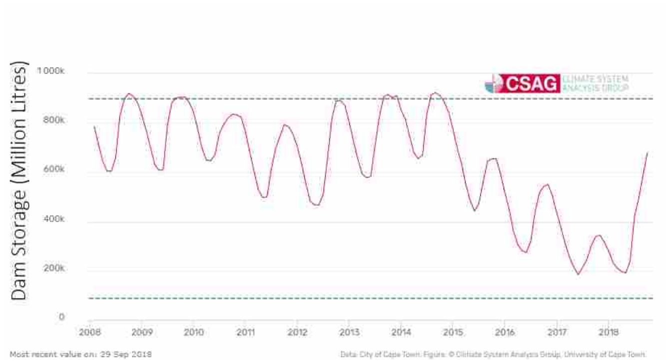


(d) 2018



When the drought continued, extreme measures were necessary to ensure subsistence levels of public water provision. In early 2018, city and provincial

FIGURE 2.
Water Level of Major Reservoirs in the Western Cape



authorities began seriously discussing "Day Zero," when water supplies would be shut off to individual homes and businesses. Water would be available only at centralized and closely monitored public distribution points. Residents would have no water piped into their homes, and would receive an allowance of just 6.25 gallons per person per day available only at those centralized locations across the city that would be monitored by police. Day Zero was initially forecasted for 16 April, 2018.

The regulations and the impending threat of Day Zero in early 2018 reduced water consumption in Cape Town enough to prevent the shut off of water. Had the water in Cape Town been shut off, it would have marked the first time in any major city in modern times that public piped water supplies would be suspended.

The appendix to this paper includes full details on the dates and details of the regulations implemented in Cape Town. The strictest regulations and the date of the Day Zero announcement correspond to year 2018 in the data set (Apr2017–Mar2018). The regulations in place during year 2017 (Apr2016–Mar2017) are comparable to the strictest constraints that have been imposed in the United

States in recent history, i.e. the 2011–2015 drought in California and the 2010–2011 drought in Texas.

Empirical Model

Data Sources

For the analysis of this paper I put together a database that combines data on crime in South Africa, precipitation, and other demographic variables at a disaggregated geographic level.

Disaggregated crime data is provided by the South African Police Service.[3] The dataset contains annual counts of the number of crimes in different categories at each police station during 2009–2018. The South African Police Service releases these data annually in September or October. For all crimes, the data consist of the number of reported crimes, rather than the number of crimes actually committed. It must be acknowledged that there may be some question as to the reliability of the crime numbers. The Ministry of Police is under a directive to reduce crime, and there is anecdotal evidence that at least some police stations under-report minor crimes to comply with crime-reduction expectations. However, the more serious crimes (such as robbery, assault, murder) are believed to be very reliable.[4] There have been many domestic news stories written about whether reductions in property crimes nationwide are the result of actual crime reductions, or merely a consequence of decreased reporting.[5] The less-serious crimes in this

[3]https://www.saps.gov.za/services/crimestats.php

[4]https://africacheck.org/factsheets/factsheet-south-africas-crime-statistics-for-2017-18/

[5]https://www.timeslive.co.za/news/south-africa/2018-09-11-are-the-saps-crimestats-accurate/

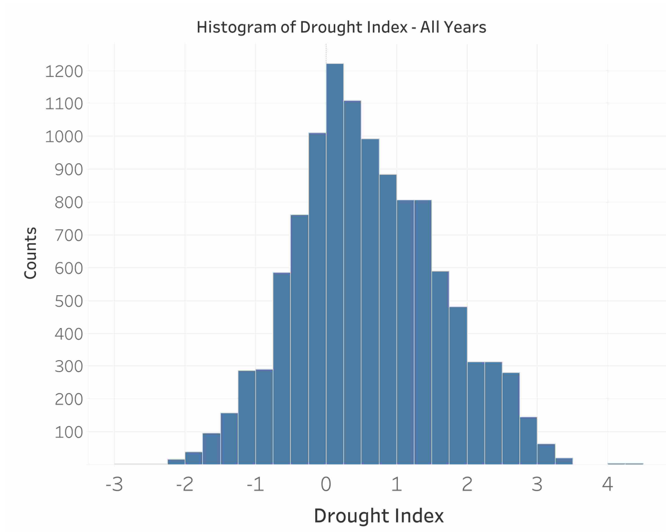
dataset therefore should be considered, potentially, to be measured with some error which will cause downward bias in the estimated impact.

There are 17 specific types of reported crimes in the dataset categorized as property crimes, sex crimes, or violent crimes. Property crimes include burglary, motor vehicle theft, arson and robbery. Sex crimes include rape, attempted rape, and sexual assault. Violent crimes include murder, attempted murder, and assault. DUI, possession of illegal firearms, and drug related crimes are also labeled as "police-detected crimes" because these are discovered by police rather than being reported.

Information on drought conditions comes from the standardized precipitation-evapotranspiration index (SPEI). SPEI is available for the entire globe at a 0.5×0.5 degree resolution for each month (Vicente-Serrano et al., 2010). The time period 1950–2010 is used to calculate the mean and variance of rainfall for standardization of each grid point. The index is measured on a scale of standard deviations. Vicente-Serrano et al. (2010) recommend that an SPEI $<$-1.5 be classified as moderate drought, and an SPEI $<$ -2.0 be classified as severe drought. I will adopt the same convention. I calculate the SPEI for each station as the weighted mean of the surrounding grid points. Figure 3 shows a histogram of the distribution of SPEI for the full sample, and Figure 4 show a histogram for individual years of the sample. The mean SPEI for the full sample is -0.6. For most years, the distribution of SPEI is approximately normal. The year 2016 is the notable exception, when a large portion of the country suffered severe drought.

I obtain control variables from Statistics South Africa (StatsSA), the government office that conducts the national census. The covariates used in this analysis include race distributions, mean income per capita, education levels,

FIGURE 3.
Histogram of Drought Index for years 2009-2018



mean household size, and the geographic area of each station's jurisdiction. I also calculate a Gini coefficient to measure inequality and a Herfindahl-Hirschman Index to measure racial concentration across the four main official racial designations in the area: Black, White, Colored, and Indian. Table 1 shows summary statistics for crime and demographic variables.

The unit of observation for this empirical analysis is the station-year, because this is the finest level of detail for the crime data. To use this level of disaggregation, the other datasets first needed to be transformed to this same spatial and temporal level of aggregation. The available drought data are matched to the geographic centroid of the station jurisdiction. The demographic data are distributed across jurisdictions using spatial weights. The appendix includes specific details about how each variable has been processed to conform to the same spatial and temporal extent.

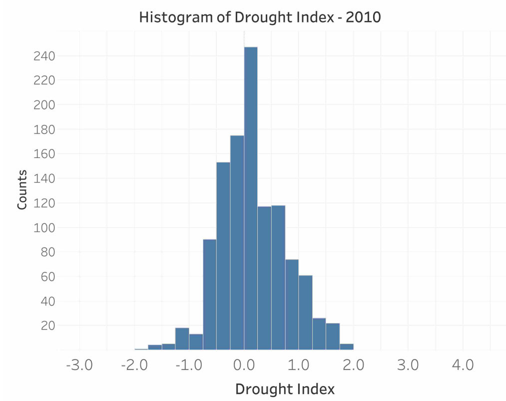
TABLE 1.
Summary Statistics

	(1)			
	Summary Statistics			
	mean	sd	min	max
Murder	15.3	23.1	0	308
All Reported Crimes	1580	2061	0	21874
Property Crimes	473	627	0	5097
Police Detected Crimes	270	465	0	7013
Population	47900	48600	349	331050
Average Income	4610	4100	960	29900
% Urban	60.7	37.2	0	100
% White	10.2	14.2	0	74.8
% Black	72.3	31.5	2.41	99.9
Observations	11400			

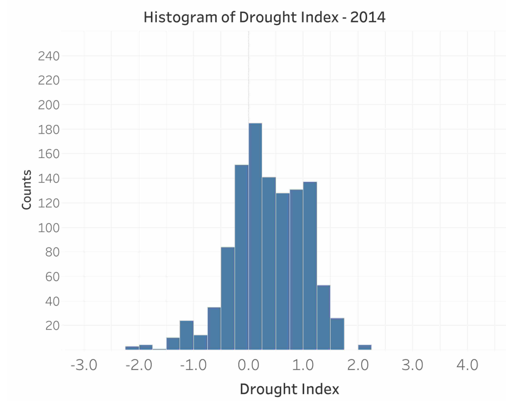
Data is annual police-station level panel data for South Africa. Crime counts is the total number reported at each station in a year. Demographic variables for the police jurisdiction are interpolated from census data.

FIGURE 4.
Histogram of Drought Index for Individual Years

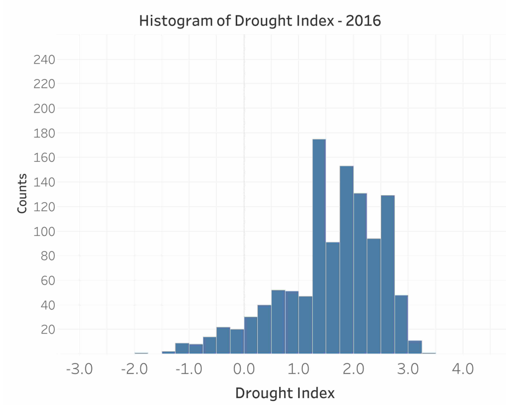
(a) 2010



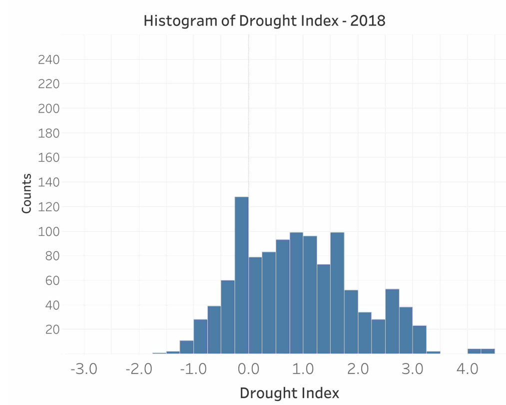
(b) 2014



(c) 2016



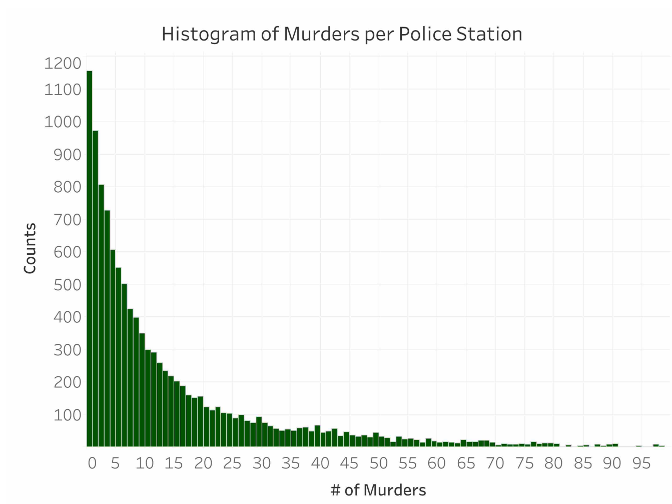
(d) 2018



Model Specification

This paper focuses on estimating the effect of extreme drought on local crime in South Africa i.e. Crime=f(Drought, Population, Avg Income, Race, ...). Figure 5 shows a histogram of the marginal distribution of the number of murders by station. Other crime types also display a similar frequency profile. The variance of this distribution is larger than the mean, indicating that a Poisson distribution will not capture the overdispersion. I assume that the numbers of crimes recorded in year t, for station i, follow a conditional negative binomial distribution. This distribution fits the count nature of the data, while generalizing the Poisson distribution to allow for over-dispersion and cross-sectional heterogeneity (Greene, 2012). Differing exposure for jurisdictions of different size is accommodated via station fixed effects.

FIGURE 5.
Histogram of Murders by Station



I choose a count-data model over the log-linear OLS approach because this allows me to accommodate both the skewness of the discrete distribution and the zero values that are prevalent in the data, particularly for some of the more uncommon crimes.

Regression Equation

The main objective of this paper is to estimate the impact of drought conditions on local crime levels in South Africa. I use a panel model, with station and year fixed effects.

The Poisson regression, a special case of the negative binomial models used here, assumes that:

$$E[\text{Crime}_{it}] = exp(\beta_1 \text{SPEI}_{it} + \beta_2 \text{Drought}_{it} + \gamma X_{it} + \alpha_i + \mu_t) \tag{2.1}$$

The dependent variable is a count variable for various types of crime collected annually over each jurisdiction over a ten-year period.[6]

I use three different measures of drought intensity, SPEI, an SPEI-based indicator for severe drought, and SPEI interacted with local water-use rationing indicators:

1. The first measure is SPEI as a continuous variable. The index is centered around 0 as an average rainfall year, negative values in the SPEI index indicate drier conditions. Negative values for the β_1 coefficients correspond to an increase in crime.

2. The second measure is an indicator variable when SPEI is less than -2, i.e when rainfall and other drought measures are two standard deviations below the long-run average. This discrete variable will account for any changes that occur when drought becomes severe. This indicator allows me to control for discrete non-linear effects that may occur only during extreme drought. The creators of SPEI recommend -2 as the threshold for severe drought, and I will follow this convention.[7]

[6]The expected number of crimes will also vary systematically with the population ("exposure") of the jurisdiction. The jurisdiction fixed effects will absorb the usual $\log(\text{pop}_i)$ explanatory variable with a coefficient constrained to unity. Changes in population are included in the X_{it} to ensure that migration does not bias the estimates.

[7]The results are robust to the exact definition of this threshold. For robustness results see the Appendix.

3. The final drought measure is an indicator whether the station is part of the specific geographic area that is affected by the emergency water restrictions imposed in the greater Cape Town metropolitan area in 2018. This variable is denoted CapeTown2018

Figure 6 and Figure 7 show the locations of areas classified using the second and third drought measures. Figure 6 shows the locations for 2011 to show the distribution for an average year, and also for 2018 when the Western Cape and other parts of the country are affected by severe drought at a higher rate than average. Figure 7 shows the locations of the police stations that are classified with the CapeTown2018 indicator. Overall, across the ten year sample period, 10.1% of the total precincts are classified with the Severe Drought Indicator, and the CapeTown2018 Indicator represents 59% of the precincts classified as Severe Drought in 2018.

FIGURE 6.
Histogram of Drought Index for Individual Years

(a) 2011 (b) 2018

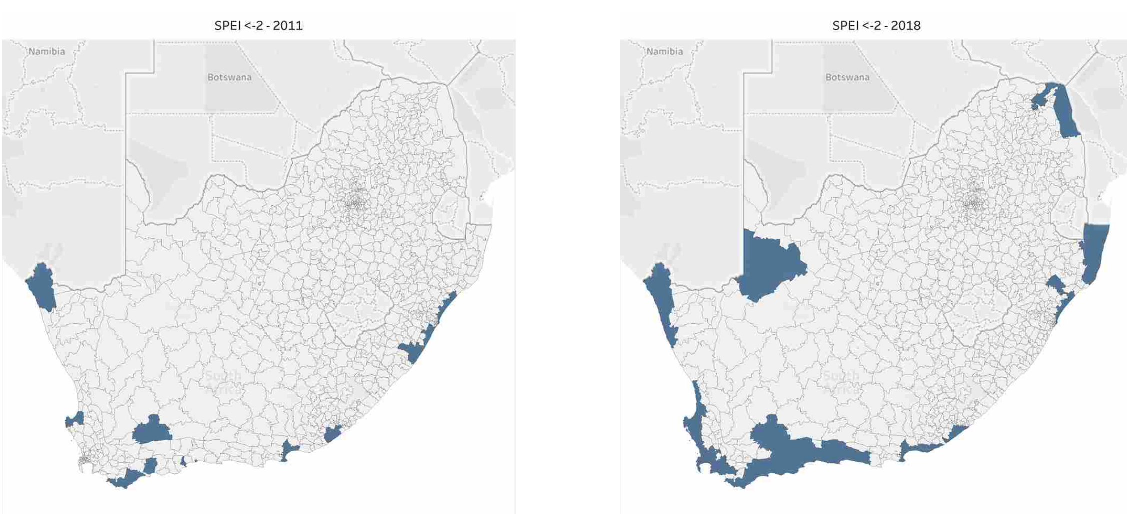
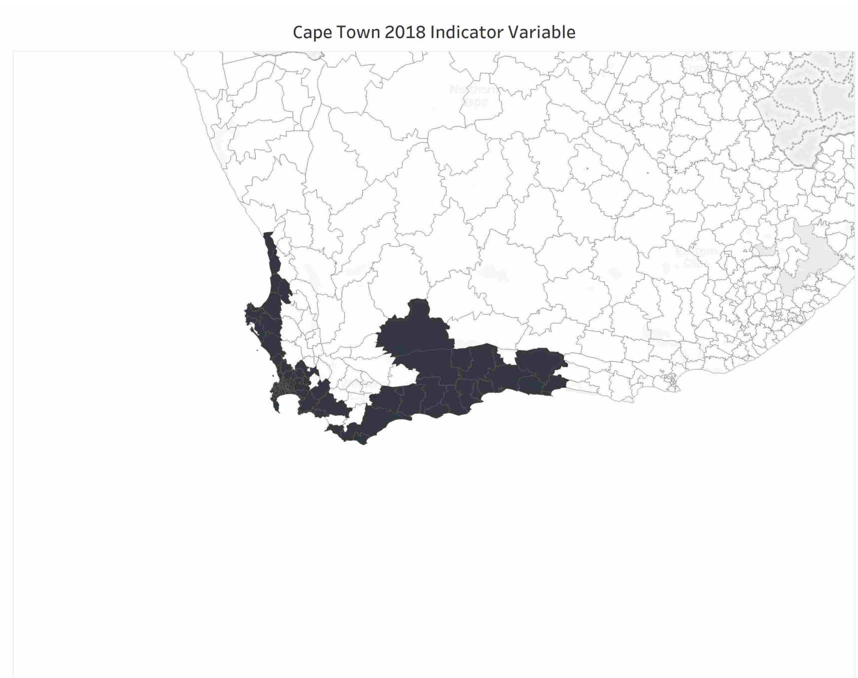


FIGURE 7.
Location of Police Jurisdictions Classified with CapeTown2018 Indicator



The term μ_t represents year fixed effects, and α_i represents station fixed effects. The station-level fixed effects control for time-invariant unobserved heterogeneity in crime at each station.[8] The time fixed effects flexibly control for any time trends or cyclical patterns in the data, shared across all jurisdictions.

The X_{it} variables are a vector of controls. These controls include population at the Province level (the finest spatial resolution available) to control for changes in crime that may be due to migration and temperature variables aggregated to the annual level.

I estimate equation (1) using maximum likelihood and calculate the standard errors via bootstrap to account for any potential serial auto-correlation in the errors (Bertrand et al., 2004; Angrist and Pischke, 2009).

The coefficients of primary interest in equation (1) are β_1, which is the effect of drought on the logarithm of crimes, and β_2, which is the change in log(crime) that occurs discretely when a station is affected by severe drought.

I next consider the effect of the Cape Town water regulations implemented in 2018 on crime:

$$E[\text{Crime}_{it}] = exp(\beta_1 \text{SPEI}_{it} + \beta_2 \text{Drought}_{it} + \beta_3 \text{CapeTown2018}_{it} + \gamma X_{it} + \alpha_i + \mu_t) \quad (2.2)$$

Equation (2) extends equation (1) by adding an indicator that equals one when jurisdictions in the greater Cape Town metropolitan area apply severe water regulations in 2018. The β_3 coefficient in equation (2) can be interpreted as the impact of the severe water regulations (and the implicitly cumulative effect of

[8]These fixed effects could be implemented at a more-aggregated level, included at the Province level, or at the district level. Districts are bureaucratic groups that oversee multiple police stations, with (on average) about ten stations per district. Table 10 shows how the results change as the spatial extent of the cross-sectional fixed effects is changed.

the lengthy drought on crime) compared to other areas that experience a severe drought (while controlling for the continuous effects of actual water availability through SPEI).

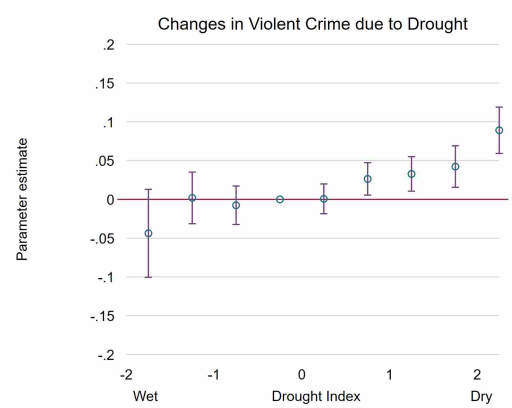
Results

First consider the effect of drought on general crime. Table 2 contains the results of estimating equation (1). The negative estimates for the coefficients of interest indicate that a one-standard-deviation reduction in SPEI (indicating drier conditions) increases violent crimes, sex crimes, aggravated robbery, and police-detected crimes by approximately 2%. However, the coefficient on SPEI for property crimes is statistically insignificant. Based on the confidence interval for the estimated coefficient, the change in property crimes for a one-standard-deviation change in SPEI is unlikely to be larger than 1.5%. Drier conditions correspond to slightly elevated levels of most crime types but do not change the levels of property crimes, on average, across police stations.

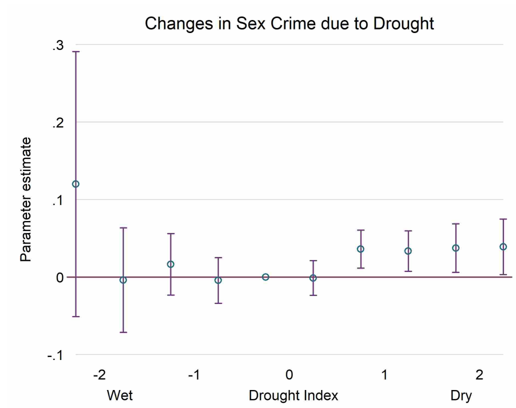
Figure 8 shows coefficients of a regression with the drought index converted into indicator variables that equal 1 if the index is within a bin of 0.5 standard deviations. This regression shows whether there are non-linear effects that are not being captured in the previous specification. The figure shows that there are increases in violent crime and robberies, and reductions in police-detected crimes when drought is severe. The figure also shows that severe wet weather may increase crime for all crime types. Across the different crime types, the linear specification fits the data well for most of the drought spectrum, and that there may be nonlinear effects for severe drought.

FIGURE 8.
Changes in Crime due to Drought: Drought Index as the Key Regressor Converted into Bins

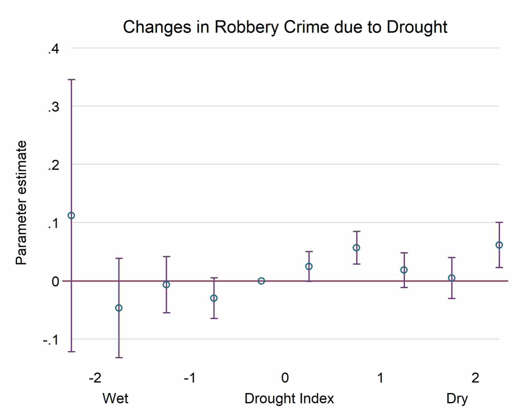
(a)



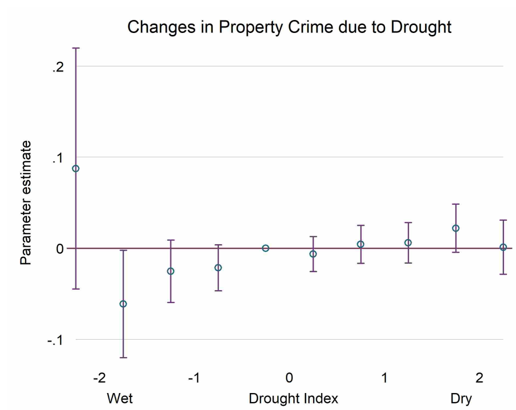
(b)



(c)



(d)



(e)

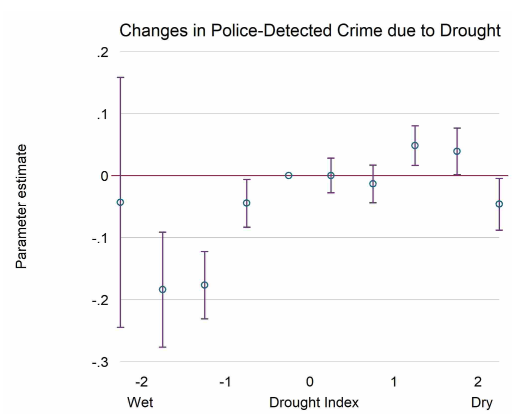


TABLE 2.
Changes in Crime by Crime Category: Drought Index as the Key Regressor

	(1) Total Violent Crimes (Excluding Sex Crimes)	(2) Total Sex Crimes	(3) Total Aggravated Robbery Crimes	(4) Total Non-Contact Property Crimes	(5) Total Crimes Detected as a Result of Police Action
Drought Index	0.0268***	0.0140**	0.0179**	0.00955	0.0171**
	(0.00677)	(0.00708)	(0.00821)	(0.00714)	(0.00711)
No. obs.	11400	11390	11310	11400	10260
Log L	-54648.13	-37081.55	-42134.06	-56449.14	-45533.23
Time FE	Yes	Yes	Yes	Yes	Yes
FE	Station	Station	Station	Station	Station
Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation.

Table 3 shows the results for estimating equation (2). The coefficient on the severe drought indicator variable tells us whether a jurisdiction that experiences a *severe* drought has a non-linear change in crime, controlling for the baseline influence of the continuous measure of SPEI. The coefficient on the severe drought indicator in the violent crime regression is statistically significant and positive. The corresponding coefficients in the police-detected crime and property crime regressions are significant and negative, but these coefficients in the sex crimes and aggravated robbery regressions are not statistically significant. These results indicate that there are discrete increases in violent crime (by about 3%) when an area faces severe drought but a decrease in reported property crimes (about 2.6%). The negative coefficients on severe drought in the regression to explain police-detected crimes is larger in absolute magnitude, indicating that police are detecting approximately 15% fewer crimes in areas that experience a severe drought. Possible explanations for why this may be the case are considered in the discussion section to follow.

TABLE 3.
Changes in Crime by Crime Category: Indicator variable for severe drought when SPEI < -2
in addition to continuous precipitation index

	(1) Total Violent Crimes (Excluding Sex Crimes)	(2) Total Sex Crimes	(3) Total Aggravated Robbery Crimes	(4) Total Non-Contact Property Crimes	(5) Total Crimes Detected as a Result of Police Action
Severe Drought	0.0318**	-0.0106	0.0234	-0.0260*	-0.145***
	(0.0127)	(0.0186)	(0.0203)	(0.0156)	(0.0219)
Drought Index	0.0220***	0.0155*	0.0141	0.0136*	0.0454***
	(0.00788)	(0.00840)	(0.00957)	(0.00812)	(0.00928)
No. obs.	11400	11390	11310	11400	10260
Log L	-54645.00	-37081.30	-42132.97	-56446.98	-45489.89
Time FE	Yes	Yes	Yes	Yes	Yes
FE	Station	Station	Station	Station	Station
Errors	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2

Table 4 shows variation in crime in the Western Cape Province over the period that had tight water rationing—beyond the drought itself—on crime. Violent crime, aggravated robbery, and crimes that are detected as a result of police action are the categories of crime that show a statistically significant change in Cape Town during the period of strict water rationing. The coefficients on violent crimes and aggravated robbery are positive, indicating that these types of crimes are increasing. The coefficeints on police-detected crimes, are negative, indicating that these types of crimes are observed less frequently.

Sex crimes and non-contact property crimes are not affected to a statistically significant extent by this rationing. However, it is possible they might experience a combination of more crime that is offset by a decrease in reporting, to yield no net effect. Splitting these crimes into their individual crime types also reveals no significant effects, as Table 8 and Table 9 in the appendix show.

TABLE 4.
Changes in Crime Types by Category: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) Total Violent Crimes (Excluding Sex Crimes)	(2) Total Sex Crimes	(3) Total Aggravated Robbery Crimes	(4) Total Non-Contact Property Crimes	(5) Total Crimes Detected as a Result of Police Action
CapeTown2018	0.0420*	0.0286	0.0828**	-0.0195	-0.204***
	(0.0226)	(0.0306)	(0.0322)	(0.0203)	(0.0352)
Severe Drought	0.00835	0.00386	-0.00289	-0.0292**	-0.119***
	(0.0128)	(0.0119)	(0.0151)	(0.0117)	(0.0216)
Drought Index	0.0174***	0.00877	0.00227	0.0115*	0.0542***
	(0.00661)	(0.00644)	(0.00954)	(0.00652)	(0.00748)
No. obs.	10260	10251	10179	10260	10260
Log L	-46602.76	-31768.98	-36234.83	-48637.73	-45470.46
FE	Station	Station	Station	Station	Station
Time FE?	Yes	Yes	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2

CapeTown2018 Variable=1 for the jurisdictions affected by strict rationing

Tables 5, 6, and 7 break these broader categories of crime into their constituent crime types.

Table 5 breaks down violent crime into murder, attempted murder, and common assault. These increase in jurisdictions under severe water rationing. Reported numbers of "assault with intent to harm" are not affected to the same extent as the other violent crimes.

Table 6 splitsf aggravated robbery into its consituent crimes. The increase in hijacking crimes in the face of stringent water rationing is quite large, at over 20%. The one type of robbery that does not show an increase in the Cape Town area affected by water rationing, is "robbery at a non-residence": businesses do not experience the same increase in robberies as individuals at home and on the street.

Table 7 shows the separate models for each police-detected crime in the Western Cape region affected by the water rationing. The coefficients on the ratioing indicator variable in the regression suggest that DUI and drug-related crimes are less likely to be detected by police, while the effect of the stringent rationing on "illegal possession of firearms" is not statistically different from zero.

Combining the percent increases from the estimated coefficients with the mean number of crimes in the stations that are affected by the stringent rationing, I calculate that the stringent rationing is associated with 335 murders, 502 car and truck hijackings, 475 robberies at residence, and that 4470 DUIs went undetected.

TABLE 5.

Changes in Violent Crimes: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) Murder	(2) Attempted Murder	(3) Assault with Intent to Harm	(4) Common Assault
CapeTown2018	0.0994**	0.149**	-0.00843	0.0975***
	(0.0398)	(0.0722)	(0.0235)	(0.0309)
Severe Drought	-0.00758	-0.0446**	0.00357	0.00766
	(0.0176)	(0.0227)	(0.0116)	(0.0133)
Drought Index	-0.00538	0.00776	0.0218***	0.00908
	(0.00958)	(0.0104)	(0.00751)	(0.00823)
No. obs.	10224	10143	10260	10260
Log L	-22140.86	-22429.24	-40388.68	-39410.54
FE	Station	Station	Station	Station
Time FE?	Yes	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2.

CapeTown2018 Variable=1 for the jurisdictions affected by strict water rationing

TABLE 6.
Changes in Aggravated Robbery Crimes: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) Car Hijacking	(2) Robbery of Residence	(3) Robbery of Non-Residence	(4) Truck Hijacking
Cape Town 2018	0.233***	0.178***	0.0514	0.778***
	(0.0696)	(0.0439)	(0.0450)	(0.146)
Severe Drought	0.0987***	0.0157	0.0472*	0.162**
	(0.0306)	(0.0198)	(0.0262)	(0.0732)
Drought Index	-0.0567***	-0.000539	-0.0209*	0.126***
	(0.0137)	(0.0107)	(0.0118)	(0.0341)
No. obs.	8532	9828	9747	5787
Log L	-15126.61	-21619.46	-22282.82	-5617.76
FE	Station	Station	Station	Station
Time FE?	Yes	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2.

CapeTown2018 Variable=1 for the jurisdictions affected by strict water rationing

TABLE 7.
Changes in Crimes Detected by Police Action: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) DUI	(2) Illegal Possesion of Firearm	(3) Drug Related Crimes
Cape Town 2018	-0.385***	0.0128	-0.216***
	(0.0472)	(0.0591)	(0.0463)
Severe Drought	-0.0913***	-0.0411*	-0.140***
	(0.0298)	(0.0224)	(0.0236)
Drought Index	0.0743***	0.00950	0.0605***
	(0.0115)	(0.0102)	(0.00931)
No. obs.	10134	9954	10242
Log L	-32836.72	-21502.85	-42641.77
FE	Station	Station	Station
Time FE?	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap

Bootstrapped standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2.
CapeTown2018 Variable=1 for the jurisdictions affected by strict water rationing

Discussion

These sets of results suggest that drought is broadly associated with increases in crime. Severe drought is associated with further increases in violent crimes, and a reduction in police-detected crimes. The strict water rationing in Cape Town is associated with a further increase in violent crime, and a further reduction in police-detected crime.

These results broadly match those of Goin et al. (2017)—that severe drought causes an increase in crime. However, the results by type of crime are different. In the California case, the drought was associated with a large increase in property crime and a small increases in violent crime.

There are a few possible explanations for this discrepancy. The California drought did not impose residential regulations as severe as those in Cape Town, focusing instead mostly on agricultural regulations. South Africa also has a higher baseline crime rate, for violent crime in particular. It is possible that both set of estimates reflect what actually happened in each region. It is also possible that the effects of drought in one region will be somewhat different for different regions at different stages of development, for different cultures, and for different baseline levels of conflict in general.

A different explanation is that the crime statistics in South Africa may not fully reflect the actual incidence of criminal behavior. The number of *reported* crimes is a function of the number of crimes actually committed and the percentage of crimes that are reported. Individuals report crime less often when they believe the police will not dedicate time to finding the perpetrator or recovering stolen property.[9] It is possible that property-based crimes could increase with the imposition of water use regulations, but that reporting rates simultaneously decrease. This could result in reported crime counts being relatively unchanged. I do not have access to any data on South African reporting rates for these crimes. As mentioned in the data section, several South African news outlets have expressed skepticism about the observation that property crimes seem to be declining nationwide. If the reporting rates are changing at the same rate across the country, the time fixed effects in the model would ensure that the estimates are unbiased. However, if the reporting rates are changing differentially

[9] http://www.statssa.gov.za/?p=11632

across drought and non-drought areas, these patterns could bias the estimates. In particular, if reporting decreases in drought-afflicted areas, we might fail to observe an increase in reported crime, even though actual crime rates increase.

One source of information help ascertain whether reporting rates may be changing in nontrivial ways. The Census Bureau of South Africa conducts an annual survey of a random sample of 30,000 households. Among the questions asked is whether the respondent has been a victim of a crime, as well as whether they reported that crime. The survey respondents reported a five percent increase from 2017–2018 in all crime including property-based crimes, while the data from the South African Police Service shows no increase. The Census Bureau survey also reports that the reporting rate for burglaries does not change. Unfortunately, the Census Bureau does not disaggregate the survey-based information by province or provide the microdata to determine whether the reporting rates are changing differentially across provinces.

Police-detected crimes show a significant reduction in drought areas compared to the rest of the country. These types of crimes are reported as a result of police setting up DUI checkpoints and observing crimes incidentally while on patrol. Police resources may be substituted away from detecting these crimes toward enforcing water usage. The police may also be aware of the increase in violent crimes and may be reallocating their more-limited resources towards solving and preventing more-serious crimes. It is also possible that we are observing a true reduction in the incidence of drug use and DUI.[10] With the current dataset, however, I cannot formally test whether occurrence or detection is decreasing.

[10] I do not have direct data on drug activity, alcohol use, or illegal firearm possession to support either option.

Differential Effects

To examine where crime responses are more pronounced, in this section I use sub-samples of the data based on demographic variables. I partition the data along one dimension at a time, into three groups defined by the 25 percentile, the 75 percentile. These separate regressions will tell us whether the effects of drought on crime are different for communities with different sociodemographic characteristics.

Figure 9 shows the results for counts of violent crime regressed on drought for subsamples according to the average income of the police jurisdiction. For the most severe levels of drought, the point estimate is the smallest for the sample with low levels of average income, and highest for jurisdictions with high levels of average income. However, these estimates are not statistically different from the full sample estimate at a 5% significance level.

Figure 10 shows the results of violent crime regressed on drought for subsamples of urbanization. For the most severe levels of drought, the point estimate is the largest for highly urban areas, and is lowest for areas that are less urban (high farm or tribal). These estimates are also not statistically different from the full sample estimate at a 5% significance level.

Figure 11 shows the results of violent crime regressed on drought for subsamples of the Gini Coefficient. The results of this subsampling do not vary the estimates in a meaningful way. The point estimates for all subsamples are similar to the full sample, and are not statistically different from the full sample estimates.

Figure 12 shows the results of violent crime regressed on drought for subsamples of the HH Index that measures racial homogeneity. For the most severe levels of drought, the point estimate is the largest for the most racially homogeneous jurisdictions, and lowest for the most racially fragmented jurisdictions. These subsampled estimates are also not statistically different from the full sample estimate at a 5% significance level.

Together these results suggest that the increase in crime due to drought is concentrated in the areas that are more urban with higher average income, and that income inequality and racial fragmentation do not drive the increases in violent crime.

FIGURE 9.
Changes in Violent Crime due to Drought. Subsamples based on Average Income of the Police Jurisdiction

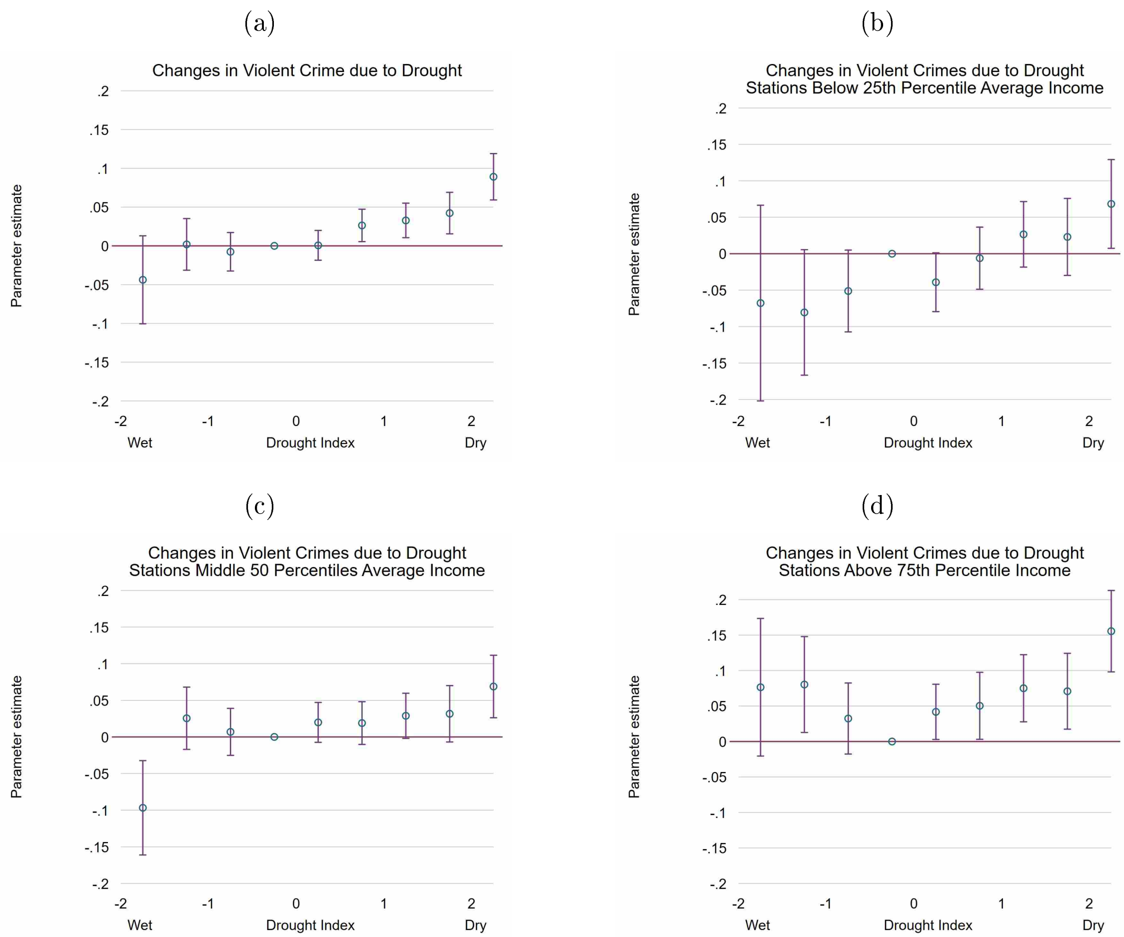
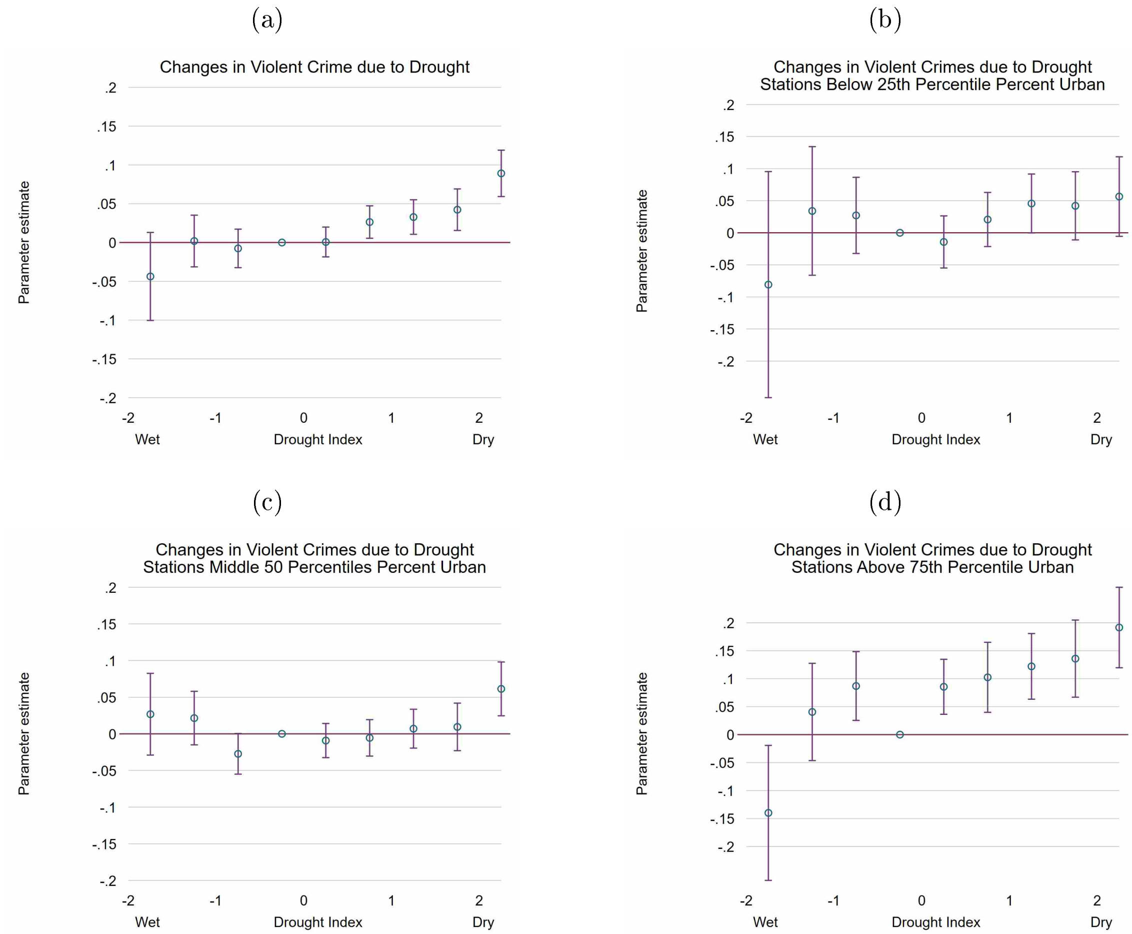


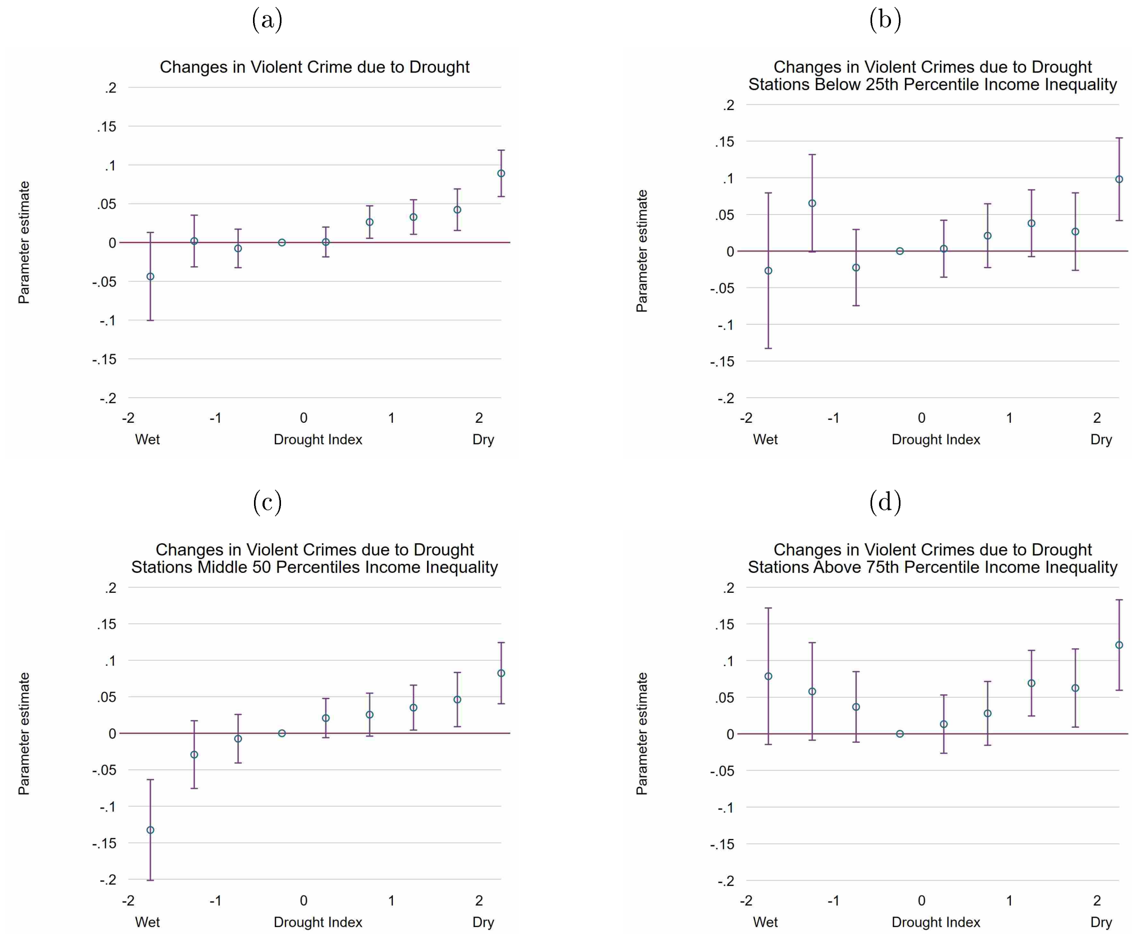
FIGURE 10.
Changes in Violent Crime due to Drought. Subsamples based on Urbanization of the Police Jurisdiction



Robustness Checks

Figure 13 shows a reproduction of Figure 8 using different methods to calculate the drought index at the station level. Inverse distance weighting of the four nearest neighbors is used in the base specification. This figure shows that using five nearest neighbors or using inverse square weighting produce results that are quantitatively similar and qualitatively identical. The figure also shows the results when the previous years drought is used instead of the present years

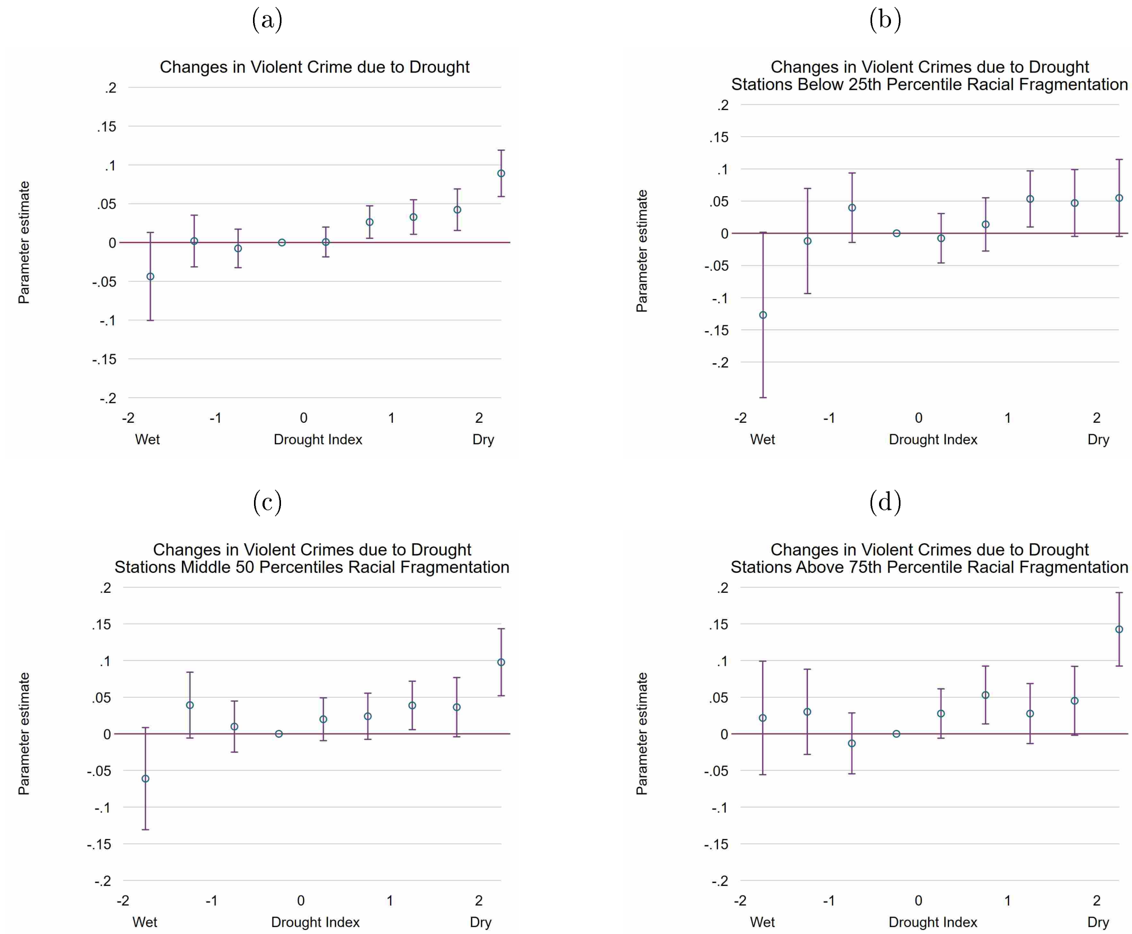
FIGURE 11.
Changes in Violent Crime due to Drought. Subsamples based on Gini Coefficient of the Police Jurisdiction



measure. The coefficient values are attenuated using the prior years drought, but have the same sign for each bin.

Figure 14 shows a placebo test consisting of a model with murder as the dependent variable, employing the three drought-related variables included in Table 4. For this figure, each year is given a dummy variable that is interacted with the stations that are within the Cape Town water-regulatory area. The specification used is negative binomial and similar to the specification used in previous models for all of the crime types. Here, however, there are multiple

FIGURE 12.
Changes in Violent Crime due to Drought. Subsamples based on HH Index (Racial Homogeneity) of the Police Jurisdiction

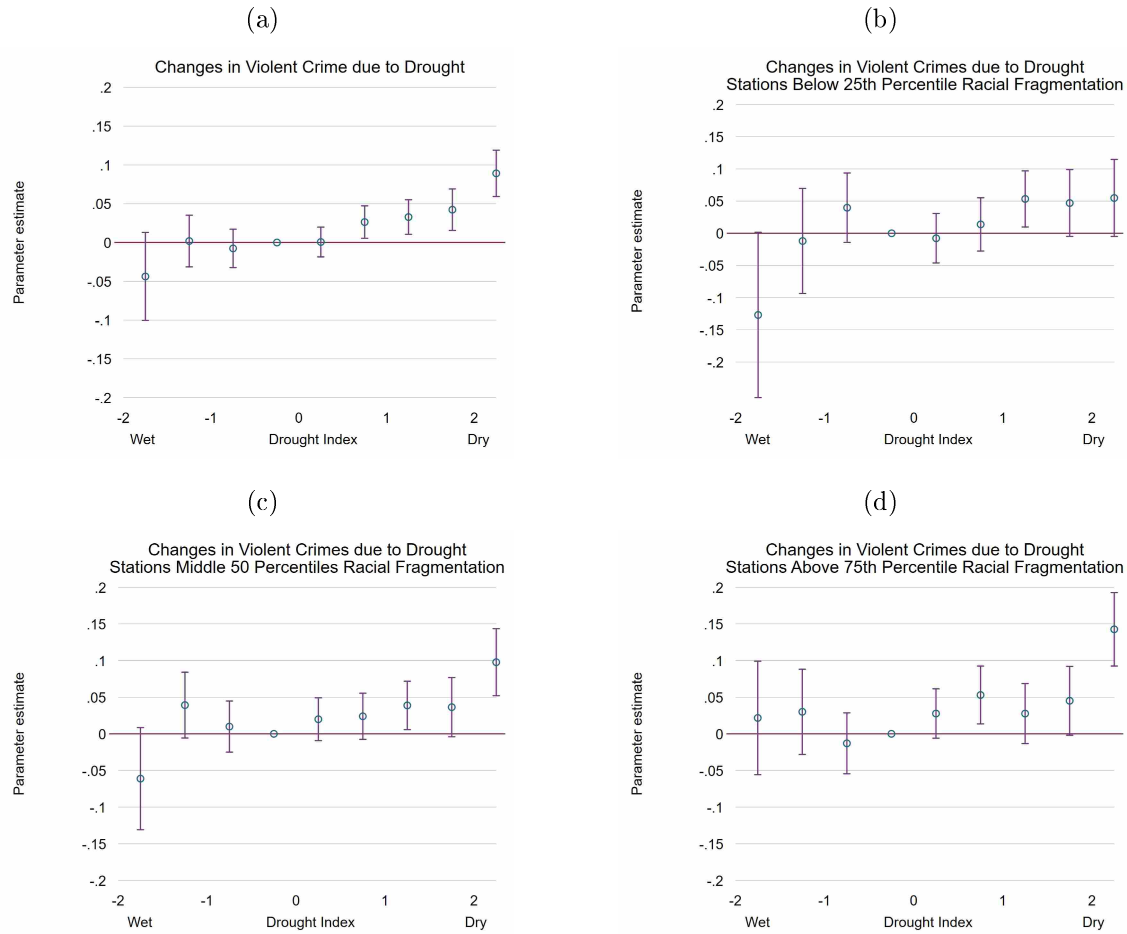


indicators for alternative ‘treatment’ years. The regression specification is:

$$E[Crime_{it}] = exp(\beta_1 SPEI_{it} + \beta_2 Drought_{it} + \sum_{s=2011}^{2018} \beta_{3s} D_s CapeTown2018_i + \gamma X_{it} + \alpha_i + \mu_t) \tag{2.3}$$

where $D_s = 1$ in year “s” and zero otherwise. The figure suggests that there was a significant difference in crime rates during for 2015, as well as 2018. The anomaly in 2015 is unexpected. This could be due to some phenomenon not observed in the data, or it could be that 2015 was the first year that any significant drought

FIGURE 13.
Changes in Violent Crimes due to Drought: Robustness to Different Calculation of Station Level Drought Index

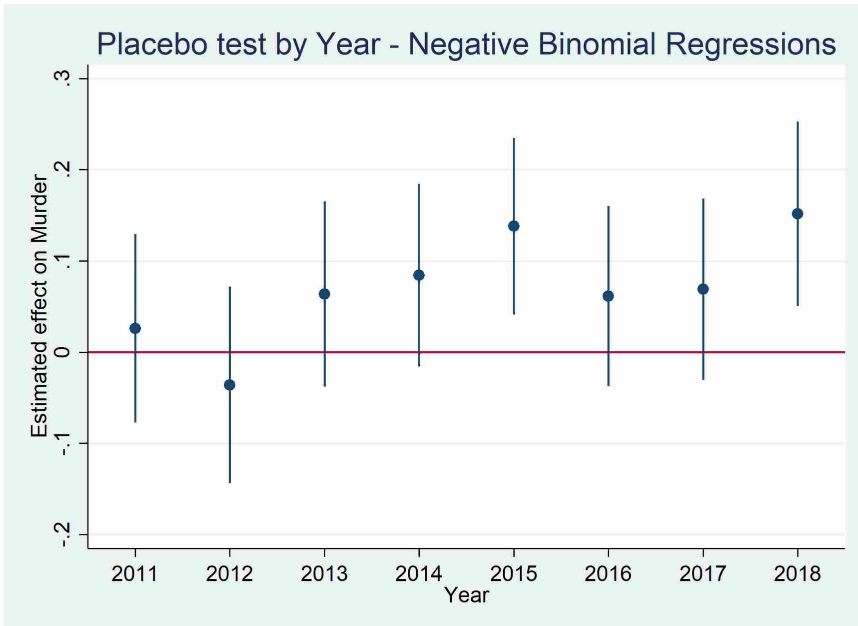


hit the area, and that the city adjusted during 2016-2017 to some resulting mild regulations, and the strict regulations implemented in 2018 caused crime to increase once again.

Future Research

The current version of this paper has two sets of results. The first set is the effect of drought in general as measured by SPEI and the second is the effects in Cape Town. Future research will put more emphasis on the general results, and

FIGURE 14.
Placebo Test Varying Time of Treatment



focus less on the results using the Capetown2018 indicator variable. The severe drought situation will be discussed as a potential mechanism for the general result.

Conclusion

This chapter examines the effect of drought on crime. I use a spatially disaggregated precipitation index (SPEI) to measure drought, and crime data from the South African Police Service, to estimate whether drought and water shortages affect crime. I find evidence that drought increases violent crimes, sex crimes, robberies, and police detected crimes by about 2% for every 1-standard-deviation reduction in rainfall, but that property crimes are unaffected. In addition, I find that the stringent rationing required to manage the drought in Cape Town was accompanied by an additional 10% increase in violent crimes and robbery, and that police-detected crimes were 20% less likely to be documented.

In addition, I test this relationship using demographic data. These results suggest that robbery-type crimes increase most in areas where incomes are higher. Future research may be able to explore potential mechanisms more fully. Microdata on crime, the victim, and the perpetrator would allow further studies to identify specifically how changes in climate and water availability affect crime.

The Intergovernmental Panel on Climate Change (IPCC) predicts that dry regions are likely to experience less rainfall in the future and that droughts will become more prevalent worldwide.[11] These results suggest that scientists who are studying and forecasting the impacts of climate change should consider the potential impacts of severe droughts on crime. Policy-makers could also consider the potential costs of crime when conducting benefit-cost analysis to inform climate-related decisions.

Appendix

Timing of Drought Regulations

February 1, 2017 - "Level 3B"

- Watering allowed only two days per week for a maximum of one hour per day
- No hoses or sprinklers allowed, only buckets or watering cans
- No washing of vehicles or boats

May 2017 - "Level 4"

[11] http://www.ipcc.ch/pdf/technical-papers/climate-change-water-en.pdf

- Consumption limited to 25 gallons per person per day
- Irrigation prohibited

July 2017 - “Level 4B”

- Consumption limited to 22 gallons per day
- Flushing toilets with greywater recommended

The next set of regulations were all implemented after the rainy season of 2017; the total available water for the dry season was known.

September 2017 - “Level 5”

- Pools banned
- Manual toilet flushing (buckets from greywater or laundry)
- Required registration of private well and boreholes
- Signage requirements when using well water or greywater for landscaping

January 2018 - “Level 6”

- Commerial properties to reduce comsumption by 45%
- Agriculture to reduce consumption by 60%
- Enforcement of residential restrictions via fines

February 2018 - “Level 6B”

- Restriction to 12.5 gallons per person per day
- Establishment of 200 water collection points across the city in preparation for residential and commercial water supplies being shut off

Data Processing

The unit of analysis is the station-year. The raw data from other sources exists at different spatial or temporal scales. This section outlines how these other data sources have been aggregated to the police station level.

SPEI

The SPEI data are gridded at 0.5 degrees of latitude and longitude, and are available in netCDF format.[12] To combine these data with the station-level crime data, I first extract the SPEI values for all available latitudes and longitudes of South Africa, and convert it to "tidy" format (Wickham, 2014). To match the SPEI values to the police station level, I first calculate the centroid of latitude and longitude for the jurisdiction of each police station. I then calculate the coordinates of the four nearest neighbors on the SPEI grid. The set of four neighbors was chosen because this provides a value in each basic cardinal direction. The section on robustness checks verifies that the basic results hold when different numbers of nearest neighbors are used. After determining the nearest neighbors, inverse-distance weighting is used to calculate the SPEI value for each police station. The formula for this calculation is:

$$\text{Station SPEI} = \frac{\Sigma \frac{z_i}{d_i}}{\Sigma \frac{1}{d_i}} \tag{2.4}$$

where d_i is the distance to the grid point i, and z_i is the SPEI value at grid point i. Inverse-squared distance is also calculated for robustness. The formula for

[12] http://spei.csic.es/map/maps.html#months=1#month=6#year=2018

inverse-squared distance is:

$$\text{Station SPEI} = \frac{\Sigma \frac{z_i}{d_i^2}}{\Sigma \frac{1}{d_i^2}} \tag{2.5}$$

The SPEI data are available at the monthly level. The corresponding annual SPEI level is calculated as the mean of the 12 monthly values from April to March, corresponding to the fiscal year for reported crime statistics. The variance was also computed for each year, but was not found to have a statistically significant slope coefficient in the regressions. Data cleaning and conformation was accomplished using MATLAB

Demographic Data

The demographic data are drawn from the South African census, as distributed by statsSA. The data for the 2011 census are available at the ward level. There are approximately six wards associated with each police station. The 2017 census is not yet available. The 2005 census and the 2016 community survey (10%) sample are available at the municipal level which is a larger spatial unit. The municipal levels are larger than the police station jurisdictions, and obtaining demographic estimates would require disaggregation rather than aggregation. I use the 2011 census as it is the only data available that is at a smaller spatial unit than the police jurisdictions.

The jurisdictional boundaries for police stations do not match perfectly with ward boundaries. Thus, areal interpolation was needed to generate demographics at the police station level. I assume that the population is distributed homogeneously across the area of each ward. For any ward that crosses two or more police jurisdictions, the proportion of the population of the ward that is assigned to each jurisdiction is assumed to be the proportion of the ward's area that lies within each jurisdiction. This strategy creates a degree of classical measurement error in the demographic variables, which will tend to bias towards zero the estimated coefficients on the interaction terms in income, race etc. The areal weights for this interpolation were constructed using ArcGIS, and the calculations were done in Stata.

Tables

TABLE 8.

Changes in Property Crimes: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) Burglary at Residence	(2) Burglary at Non-Residence	(3) Vehicle Theft	(4) Other Theft	(5) Malicious Damage to Property	(6) Shoplifting	(7) Arson
Cape Town 2018	0.0137	-0.0310	0.0238	-0.0185	0.0539	0.0499	0.380***
	(0.0222)	(0.0348)	(0.0419)	(0.0365)	(0.0510)	(0.0574)	(0.0545)
Severe Drought	-0.0260**	-0.0293**	-0.0378*	-0.0226*	0.0177	-0.0777*	0.0923***
	(0.0118)	(0.0145)	(0.0224)	(0.0129)	(0.0189)	(0.0421)	(0.0339)
Drought Index	0.0193**	-0.0145**	0.0216*	0.0213***	0.00779	0.00508	0.00416
	(0.00758)	(0.00606)	(0.0124)	(0.00696)	(0.00585)	(0.0183)	(0.0121)
No. obs.	10260	10206	10125	10260	11400	8631	9918
Log L	-42465.52	-33636.72	-25620.47	-47618.28	-39728.72	-24623.67	-16676.64
FE	Station	Station	Station	Station	Station	Station	Station
Time FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap	Bootstrap

Standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2.
CapeTown2018 Variable=1 for the jurisdictions affected by strict water rationing

TABLE 9.

Changes in Sex Crimes: Continuous and Discrete Measures of Drought and Water Regulations in Cape Town

	(1) Rape	(2) Sexual Assault	(3) Attempted Sexual Assault
Cape Town 2018	-0.00786	0.0306	0.260***
	(0.0314)	(0.0422)	(0.0802)
Severe Drought	0.00107	0.0137	0.0444
	(0.0146)	(0.0261)	(0.0401)
Drought Index	0.0121*	-0.0293**	0.00488
	(0.00733)	(0.0129)	(0.0146)
No. obs.	10242	10071	9810
Log L	-29350.98	-17791.22	-13505.49
FE	Station	Station	Station
Time FE?	Yes	Yes	Yes
Clustered by:	Bootstrap	Bootstrap	Bootstrap

Standard errors in parentheses

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

Note: All regressions include Year and Station fixed effects, and changes in population at the provincial level. Drought Index used is SPEI, measured as standard deviation from mean precipitation. Severe Drought Indicator=1 when SPEI <-2.
CapeTown2018 Variable=1 for the jurisdictions affected by strict water rationing

CHAPTER III

THE IMPACT OF DROUGHT ON MIGRATION IN THE UNITED STATES

Introduction

Climate change is predicted to increase water scarcity and to cause droughts to become more prevalent and intense (Gleick and Heberger, 2014). As a result of increased water scarcity, some households may be compelled to reconsider where they choose to live and work. Recent attention has focused on how drought and heat have influenced international migration (Barrios et al., 2006; Mayda, 2010; Cai et al., 2016; Cattaneo and Peri, 2016; Baez et al., 2017). However, there are approximately three migrations within a country for every international migration (McAuliffe, 2017), so it is crucial to also understand the subnational influence of climate change on migration.

Previous empirical work that has looked at developing countries onlyhas found mixed results concerning whether drought and climate influence migration. Several studies find that drought and temperature increase migration, others find no influence, and some have found that drought leads to reduced migration caused by households stuck in a liquidity trap. These different outcomes may be due to the different ways drought and heat affect areas with different levels of development. Places dependent on agriculture are more affected by climate change and thus may be more prone to climate-induced migration. Places with a greater level of development are more resilient and may be be less-affected by climate change because of the availability of insurance, the existence of a social safety net, and greater opportunity to substitute for deficient rainwater with groundwater (Hornbeck and Keskin, 2018).

To address this question I use a dataset of annual county-to-county migration flows for each county in the United states from 2000 to 2013. I first estimate migration between each pair of counties using a fixed effects model that controls for unobserved time-invariant factors that determine the migration rates between the pair. I find that moderate and severe drought do not seem to influence migration overall, but that exceptional drought appears to cause a reduction in out-migration. I also find that three consecutive years of moderate or higher drought leads to a 2-3% reduction in out-migration. This is consistent with droughts causing reductions in income or wealth that lead to liquidity constraints.

To explore further this relationship, I re-estimate these regressions using different subsamples of my data based on demographic variables (proportions, typically) at the county level. I find that consecutive years of drought tends to reduce out-migration from places with lower than average median income, higher than average poverty, and a higher than average proportion of foreign-born individuals.

While there is a nascent literature examining how temperature and weather affect migration, to my knowledge there have been no prior works that examine whether drought affects migration choices within the United States or other more-highly developed countries. These results suggest that drought does not drive out-migration in the United States to the extent found in developing countries. This suggests that adaptation through migration is not likely to play a strong role in reducing climate change damages in the United States These results can inform climate policy in the United States. If drought-induced migration will be limited, public policy may need to direct necessary aid those affected by severe drought who are less able to adapt by moving to a different area.

The paper proceeds as follows: Section 2 provides background on the link between drought and climate and migration. Section 3 describes my data sources and outlines the model used to estimate the impact of drought on migration. Section 4 describes the results discusses their implications. Section 5 concludes.

Literature Review

Climate change is predicted to have wide-ranging social and economic impacts, especially in developing countries. Prvious research has explored how climate, temperature, and drought have influenced health, agricultural yields, energy supplies, population, trade, and migration (Carleton and Hsiang, 2016; Dell et al., 2014). How climate and natural disasters influence migration decisions has also been studied extensively and reviewed in Millock (2015) and Berlemann and Steinhardt (2017). These reviews stress that modern econometric methods, using bilateral migration data and fixed effects estimators provide the most reliable results by controlling for endogeneity in the migration decision between locations.

The influence of drought on migration has been studied in several different locations including Asian and African countries. These studies have typically examined less developed countries (De Haan et al., 2002; Gray and Mueller, 2012; Hassani-Mahmooei and Parris, 2012; Lewin et al., 2012; Drabo and Mbaye, 2015; Alam et al., 2016; Koubi et al., 2016; Ng'ang'a et al., 2016; Taraz, 2017; Grace et al., 2018; De Longueville et al., 2019). In many of these papers, it is stated that high-development countries would not expect to see the same levels of drought and climate induced migration.

The theoretical underpinnings of migration were established by Roy (1959) and Borjas (1989). In the midel, individuals choose whether to migrate in order to maximize their own utility subject to their income at each location (net of moving costs). They also consider other factors such as cultural differences, politics, public goods, and the locations of family and friends. The individual migrates if their expected utility is higher in the destination than in the origin (Clark et al., 2007; Mayda, 2010). Beine and Parsons (2015) further develop the basic model to allow for individuals to fall in a poverty trap. This situation is defined as when there could be positive returns to migration, but the individual cannot afford the initial moving costs. If poor environmental or climate conditions occur in a place where these constraints are present, the climate-induced income reductions would cause the trap to become stronger and reduce migration rates.

Climate change has become a pressing issue, and a recent literature has developed to analyze how changes in climate and environmental conditions affect migration decisions. This topic has been studied mainly in the setting of developing countries where populations could be the most vulnerable to climate change. Marchiori et al. (2012) investigate whether rain and temperature anomalies in Sub-Saharan Africa affect internal or international migration, and find that both types of migration increase. Dallmann and Millock (2013) find that increased frequencies of drought increase migration by about 2% for every consecutive month of drought in India. However, they find that the magnitudes and durations of the droughts do not matter. Kubik and Maurel (2016) find that medium-income and high-income households in Tanzania migrate in response to drought but poor households are less likely to do so, indicating the possible presence of liquidity traps. Baez et al. (2017) find that unskilled workers migrate more due to drought in Central American and the Caribbean. Alam et al. (2016) find that the poor, the landless, and the less educated migrate most in response to climate in Bangladesh. Drabo and Mbaye (2015) examine how drought and other natural disasters affect international migration from developing countries to the OECD and conclude that drought increases the rate of "brain drain" from developing countries.

There have also been studies which find that drought and climate cause reductions in migration. Lewin et al. (2012) find a 21% reduction in out-migration for areas that have experienced recent drought conditions in Malawi and Grace et al. (2018) find that low rainfall reduces out-migration in rural Mali. Both Malawi and Malu studies propose that the drought reduces income so that individuals are then unable to pay the costs necessary to migrate.

Some recent papers have specifically examined the role of agriculture in climate-induced migration. Cai et al. (2016) find that internal migration is influenced only by temperature in the most agriculture-dependent countries. Cattaneo and Peri (2016) use a similar estimation strategy to infer that higher temperatures increase rural-to-urban migration in middle-income countries, but they reduce the probability of migration in poor countries.

There have been few studies that examine how climate change affects migration in the context of high-income countries. Feng et al. (2015) examine how temperature influenced migration in the United States, and they find that a measurable effect is present only in corn-belt states. The present paper adds several dimensions to that earlier analysis. I leverage my data on bilateral migration patterns to include origin-county pair fixed effects instead of just origin fixed effects. My dataset also has finer temporal resolution with annual migration instead of a five-year timescale. I also examine the effect of drought using the Palmer Index instead of just extreme temperatures.

Data

I use the annual IRS statistics of Income (SOI) data on bilateral county-to-county migration flows within the United States for the tax years 2000–2013. The data consists of counts of tax returns that report a county change in the primary address during the tax year. Due to privacy concerns, the data are censored if there are less than 10 migrations for a county pair. The majority of the analysis in this paper uses a balanced panel dataset that includes all county pairs having had 10 or more migrations for all 14 years in the dataset. This dataset thus contains 14 years of data for 46,383 county-pairs for a total of 649,362 observations.[1]

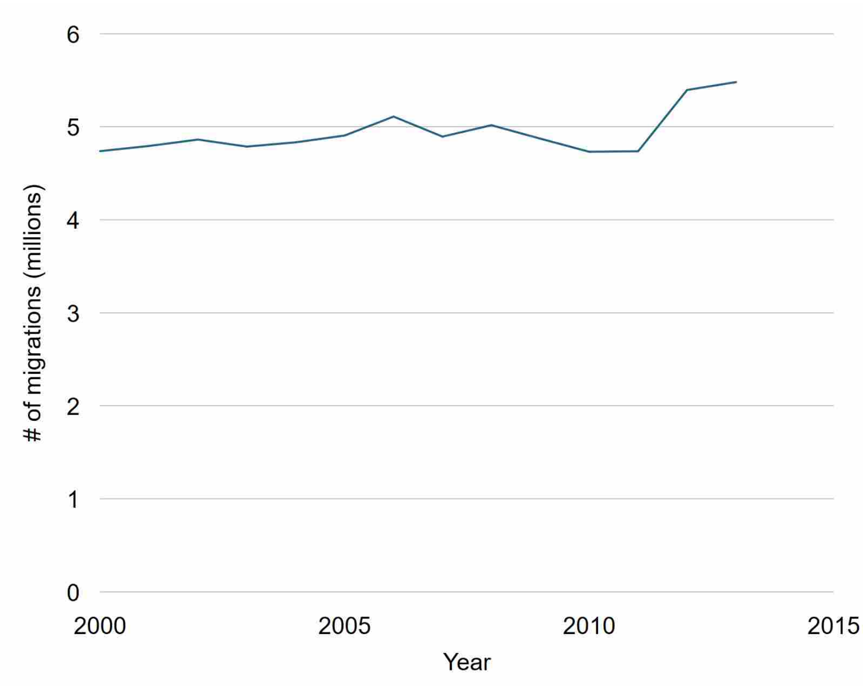
Figure 15 shows the time series of total migrations in the SOI data. The figure shows that there is a general upward trend in the number of migrations, but that the years 2009–2011 had a reduction. Several papers have documented that the Great Recession temporarily reduced migration (Kothari et al., 2013; Ravuri, 2017).

The drought measure I use is the U.S. Drought Monitor (USDM) developed by the USDA and the University of Nebraska-Lincoln.[2] This index is created using a variety of inputs to fully capture local conditions. The inputs include the Palmer Drought Severity Index and the Standardized Precipitation Index that measure rainfall compared to historical averages. The USDM also incorporates soil moisture

[1] My analysis is thus limited to explanation of "significant" internal migration flows for the U.S. Furthermore, while the data continue past the 2013 tax year, the censoring is changed to report migration only if 20 or more households migrate. In future work, it will be possible to combine both levels of censoring explicitly in the model.

[2] https://droughtmonitor.unl.edu/Data/DataDownload.aspx

FIGURE 15.
Number of Migrations within the United States over time

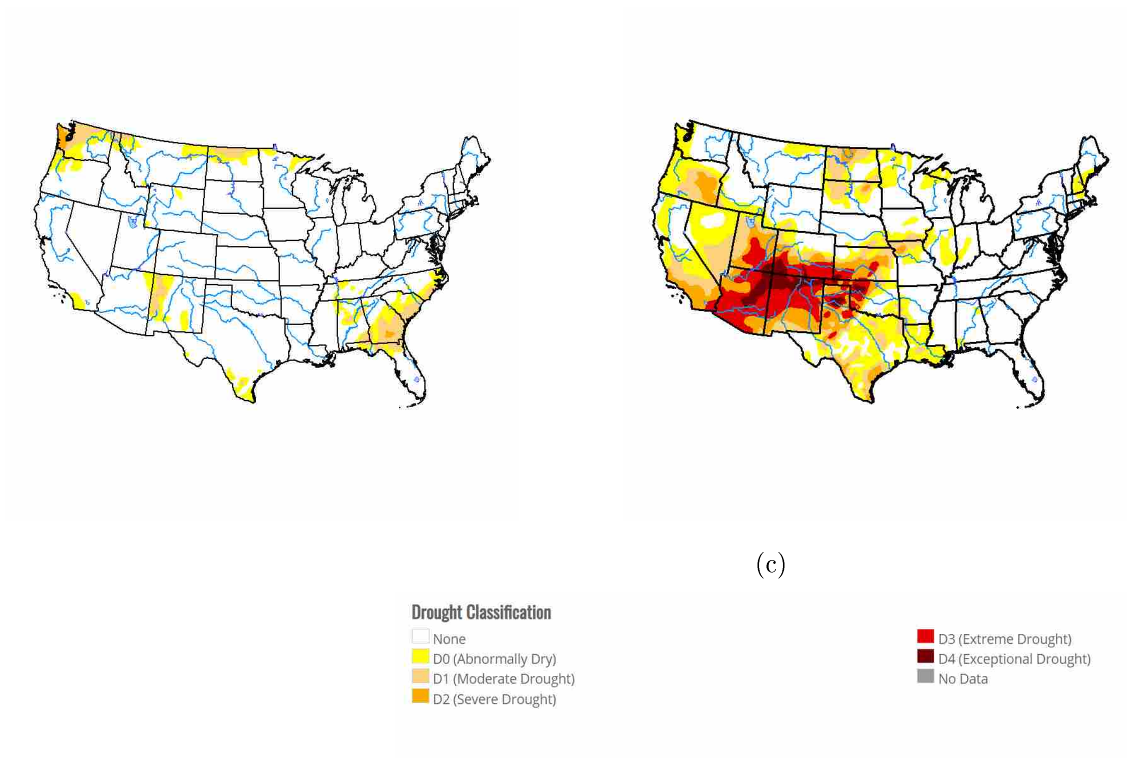


models, satellite based assessments of vegetation health, and measures that help assess local conditions such as mountain snowpack and surface water supply. Drought is classified in four categories according to increasing severity, moderate, severe, extreme, and exceptional. Figure 16 shows a map of the USDM for the continental United States comparing June 2019, a time of minimal drought to June 2018 when drought was more prevalent, particularly in the southwest.

The drought data include the percentage of the population that is exposed to drought for each county in the United States. To calculate this measure, the USDM determines the number of people that live in each classification area based on US census data and then aggregate to the county level. These data are available monthly, and for this paper have been aggregated for each origin and

FIGURE 16.
Map of US Drought Monitor

(a) (b)



destination pair by computing the mean for the twelve months between each tax deadline, when changes in county of residence are recorded by the IRS.[3] Table 10 shows summary statistic for the various drought measures and other variables

Figure 17 shows a time series of population exposure to “severe” drought over time. Comparing this time series to Figure 15 we can see that, on aggregate, the number of migrations is not determined exclusively by drought conditions. Although total migrations are not obviously driven by drought exposure, drought may influence migration behavior for selected subgroups of the U.S. population.

[3]The standard deviation was also calculated, but was not significant in any regression. So all results use the mean only

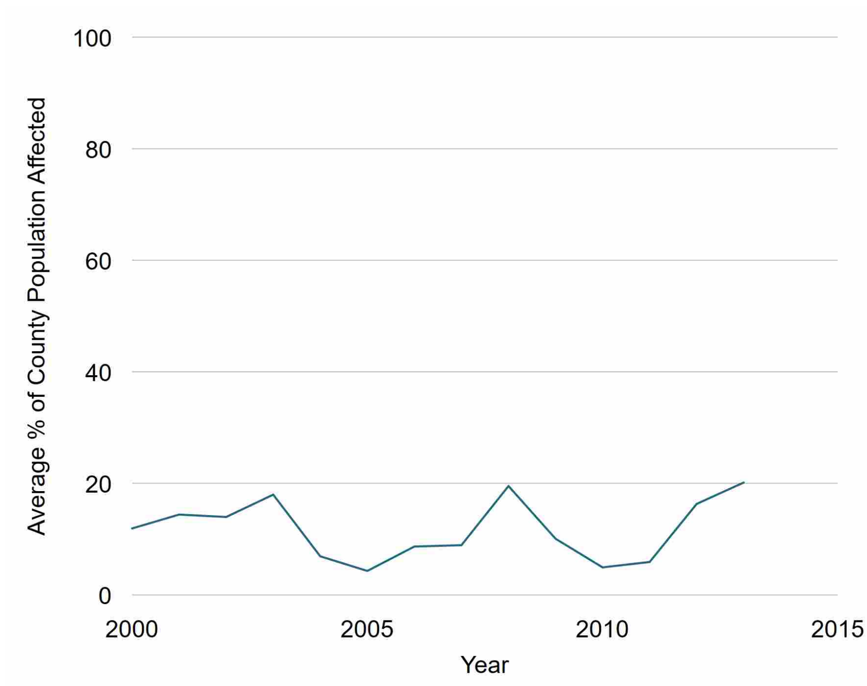
TABLE 10.
Summary Statistics

	(1) . mean	sd	min	max
Rate of Out-migration (per 10,000)	7.9	17	0.011	660
Origin: Population (Thousands)	658	1180	2.2	9520
Origin: Prop. pop abnormally dry	15.8	15.5	0	100
Origin: Prop. pop mod drought	11.1	15.7	0	100
Origin: Prop. pop severe drought	7.25	14.5	0	100
Origin: Prop. pop extreme drought	3.38	10.5	0	100
Origin: Prop. pop exceptional drought	1.09	6.38	0	96.2
Destination: Prop. pop abnormally dry	16.0	15.5	0	100
Destination: Prop. pop mod drought	11.4	15.8	0	100
Destination: Prop. pop severe drought	7.53	14.8	0	100
Destination: Prop. pop extreme drought	3.55	10.7	0	100
Destination: Prop. pop exceptional drought	1.17	6.60	0	96.2
Observations	649362			

Note: An observation is an Origin-Destination pair by year.
There are 2870 Origin Counties and 2818 Destination Counties

To discern the incremental effect of drought on migration, it is appropriate to control for other types of climate-related severe weather, as well as demographics at the county level. Disaster data are obtained from SHELDUS.[4] Demographic data for each county is obtained from the American Community Survey.[5]

FIGURE 17.
Average percent of population that is affected by severe or higher drought within the United States over time



[4]https://cemhs.asu.edu/sheldus

[5]https://www.census.gov/programs-surveys/acs

Empirical Model

To investigate the relationship between migration decisions and drought, I estimate the following fixed effects regression model:

$$\ln(\#\text{ Migrations})_{ijt} = \beta_0 + \beta_1 \text{Drought}_{it} + \beta_2 \text{Drought}_{jt} + \beta_3 X_{it} + \beta_4 X_{jt} + \alpha_{ij} + \delta_t + \varepsilon_{ijt} \qquad (3.1)$$

Where $(\ln\#\text{ Migrations})_{ijt}$ is the natural logarithm of the number of migrations between origin county i and destination county j during tax year t for this set of "significant" migration flows. Drought_{it} and Drought_{jt} are measures of drought in the origin and destination counties respectively in year t. Various drought measures are used, including the continuous measure of the percentage of the population that is exposed to drought, as well as discrete variables indicating the county is exposed to a certain severity of drought. X_{it} and X_{jt} are control variable for the origin and destination counties in year t and include demographics for the county, employment values, as well as natural disasters.[6]

The α_{ij} are origin-destination county fixed effects. These fixed effects will control for factors that could influence the number of migrations such as the populations of the origin and destination, distance, urbanization, as well as unobservable factors such as historical and cultural closeness. This model allows me to estimate the changes in migration due to drought within each county pair. The δ_t are time fixed effects to control for any time variation that is constant across all county pairs. The error term, ε_{ijt} is clustered at the origin-state and destination-state level unless otherwise specified. The key parameters of interest

[6] The natural disasters that are controlled for include flooding, hailstorms, heat waves, hurricanes, severe storms, tornadoes, wildfires, and wind storms, and severe winter weather

are β_1 and β_2 which capture changes in migration flows due to drought in the origin and destination counties.

To explore whether changes in migration are driven systematically by socio-economic conditions, I estimate the main regression using subsamples based on demographics in the origin county. The results of these regressions will allow me to determine whether drought on migration may have disproportionate effects on specific subgroups of the population.

Results

Table 11 shows the results of a regression of county-to-county migration flows on various factors that may contribute to migration. The first column shows the results of an OLS regression of the number of migrations on factors that may contribute to that migration decision. These results show that the number of migrations decreases with distance, and decreases further when the destination is not in the same state. Higher population in origin and destination counties results in more migrations. The coefficients on the demographic variables suggest that people below the poverty line and people above the age of 65 migrate less often, and that people migrate more often from places that are more urbanized and that have higher average wages.

The coefficients on the destination variables suggest that people migrate into places that have low poverty rates and higher average wages. They also migrate into places that have high urbanization, but that are less urbanized than their origin. The proportion of people that are over 65 does not have a statistically significant coefficient, indicating this does not influence their destination choice.

The second column shows the results with the addition of a indicator variables that take a value of 1 if severe or worse drought affects 25% of the county population. The coefficients on the drought variables are both insignificant, and the coefficients on the control variables are relatively unchanged.

The third and fourth column add fixed effects at the origin county and the destination county respectively. Most of the coefficients are relatively unchanged. The one coefficient that does change is that with origin fixed effects the destination county being more urban is significant and positive. The coefficients on the drought varaibles remain insignificant with the addition or these fixed effects.

Table 12 shows the results of the panel model with fixed effects for each origin-destination pair. In this model, the control variables shown in Table 11 are subsumed by these fixed effects. Fixed effects for each origin-destination pair also control for any other non time-varying characteristics of each pair of counties that may be unobservable, such as cultural or historical distance. In this model, the drought variables are continuous variables for the percentage of the population of each county that is affected by drought. The droughts are categorized as moderate drought, severe drought, extreme drought, or exceptional drought.

Column (1) in Table 12 shows the results for the full sample. Drought in the origin does not appear to have an effect on the choice to migrate, as all the categories of drought have insignificant coefficients. The coefficient on abnormally dry is significant and positive. The coefficients on drought in the destination county do have some significance, and are negative, suggesting that people are less likely to move to counties when the destination county is experiencing a drought. The potentially surprising result in this table is the positive coefficient to the most severe category of drought in destination counties and the negative coefficient

TABLE 11.
Factors that Determine Migration

	(1) ln(# Migrations) No FE	(2) ln(# Migrations) No FE	(3) ln(# Migrations) Origin County FE	(4) ln(# Migrations) Destination County FE
Distance(1000 miles)	-0.245***	-0.245***	-0.310***	-0.341***
	(0.0434)	(0.0434)	(0.0357)	(0.0296)
Origin: Population (100,000 people)	0.0118***	0.0118***		0.0148***
	(0.00239)	(0.00239)		(0.00271)
Origin: Percent below poverty line	-0.00532***	-0.00532***		-0.00521*
	(0.00168)	(0.00169)		(0.00284)
Origin: Prop. pop 65+	-0.00651**	-0.00651**		-0.0117***
	(0.00322)	(0.00322)		(0.00275)
Origin: Prop. Urban	0.0842	0.0842		0.306***
	(0.0572)	(0.0571)		(0.0748)
Origin: Payroll per employee	0.0169***	0.0170***		0.0489***
	(0.00514)	(0.00512)		(0.0162)
Destination: Population(100,000 people)	0.0127***	0.0127***	0.0155***	
	(0.00273)	(0.00273)	(0.00293)	
Destination: Percent below poverty line	-0.00625***	-0.00624***	-0.0111***	
	(0.00181)	(0.00182)	(0.00218)	
Destination: Prop. Urban	0.0434	0.0436	0.185*	
	(0.0611)	(0.0610)	(0.0935)	
Destination: Payroll per employee	0.0186***	0.0185***	0.0328**	
	(0.00592)	(0.00589)	(0.0156)	
Destination: more urban	-0.0198	-0.0199	0.106**	-0.0594
	(0.0355)	(0.0356)	(0.0467)	(0.0371)
Destination: Prop. pop 65+	-0.00571*	-0.00572*	-0.00501	
	(0.00305)	(0.00305)	(0.00492)	
SameState	0.497***	0.497***	0.869***	0.889***
	(0.0244)	(0.0244)	(0.0470)	(0.0507)
Any Drought in Origin		0.00217	-0.0115	0.00488
		(0.0108)	(0.0193)	(0.0205)
Any Drought in Destination		-0.00383	0.0220	-0.00509
		(0.0134)	(0.0299)	(0.0131)
No. obs.	578350	578350	157404	155774
Time FE	Year	Year	Year	Year
FE	None	None	Origin County	Origin County
Clustering	Orig/Dest State	Orig/Dest State	Orig/Dest State	Orig/Dest State

Standard errors in parentheses
Column (1) shows factors that may influence migration with no fixed effects. Column (2) adds dummy variables at the origin and destination county if more than 25% of the population if affected by drought.
Column (3) includes origin fixed effects and Column (4) includes destination fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

on the exposure in the origin county, although this coefficient is not statistically significant.

Columns (2) and (3) in Table 12 show the same regression results when the sample is limited by origin county to the 40% most rural and 40% lowest median income counties. For these subsamples, the coefficient on exceptional drought in the origin is significant and negative indicating that lower income and more rural areas may be exposed to liquidity traps. Otherwise, the coefficients are similar across the different subsamples.

TABLE 12.
Changes in ln(Migration) due to Drought

	(1) Full Sample	(2) More Rural Counties	(3) Poorer Counties
Origin: Prop. pop abnormally dry	0.0411***	0.0211**	0.0154
	(0.00922)	(0.00899)	(0.00949)
Origin: Prop. pop mod drought	0.0219*	0.0108	0.0203*
	(0.0129)	(0.00981)	(0.0117)
Origin: Prop. pop severe drought	0.00853	0.00145	0.00260
	(0.00934)	(0.00982)	(0.00828)
Origin: Prop. pop extreme drought	0.0191	0.0271**	0.0156
	(0.0135)	(0.0134)	(0.0184)
Origin: Prop. pop exceptional drought	-0.0434	-0.0474**	-0.0805***
	(0.0285)	(0.0220)	(0.0272)
Destination: Prop. pop abnormally dry	-0.0286**	-0.0147	-0.0261**
	(0.0117)	(0.00987)	(0.0113)
Destination: Prop. pop mod drought	0.000734	-0.00381	0.00989
	(0.0102)	(0.0101)	(0.0105)
Destination: Prop. pop severe drought	-0.0348***	-0.0107	-0.0226*
	(0.0131)	(0.0105)	(0.0122)
Destination: Prop. pop extreme drought	-0.00423	-0.00777	0.00631
	(0.0126)	(0.0128)	(0.0131)
Destination: Prop. pop exceptional drought	0.0950***	0.0690***	0.0655**
	(0.0324)	(0.0226)	(0.0271)
No. obs.	649362	260120	245084
FE	Orig-Dest pair	Orig-Dest pair	Orig-Dest pair
Time FE?	Yes	Yes	Yes
Clustered by:	Orig & Dest State	Orig & Dest State	Orig & Dest State

Standard errors in parentheses

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

Other control variables include flooding, hailstorms, heat waves, hurricanes, severe storms, tornadoes, wildfires, and wind storms, and severe winter weather in origin and destination counties.

Omitted Categories: Origin: Prop. pop no drought and Destination: Prop. pop no drought

Figure 18 shows the effects of drought on migration when the drought is measured as a single discrete indicator. This will allow me to test the effects of multi-year drought events. This variable takes a value of 1 if some percentage of the origin county's population is exposed to "moderate" or worse drought and 0 otherwise. Each figure summarized the key coefficient estimate from each of 20 separate models that occurs as the threshold of exposed population is varied from 5% to 95%. Figure 18a shows the coefficients for different proportions of "moderate" or worse drought *in just the same year* as the migration. The parameter estimate is insignificant for all values of the population threshold.[7].

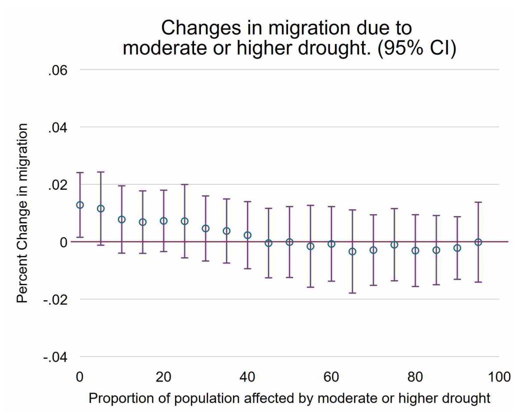
Figure 18b-d show the results of a similar regression, but the indicator variable for drought takes a value of 1 if there are two, three, or four consecutive years of drought. There is suggestive evidence that two consecutive years of drought reduces out-migration as more of the county population is affected. This evidence becomes stronger when there are three years of drought, as the negative coefficient is significant when the threshold is designated as 40 percent or more of the population. Four consecutive years of drought has a similar result, but the parameters are measured with larger error due to fewer counties being affected by drought for this long.

Figure 19 Shows a reproduction of Figure 18c, for exposure to three consecutive years of drought with subsamples of the origin counties. Each subsample is the top 40% of the origin counties according to a specified demographic variable in the benchmark year of, 2007. The figures shows that origin counties with larger shares of households with low income, high rates of

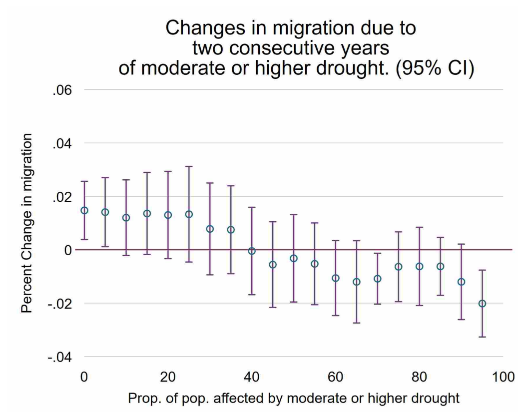
[7]Migration may have occured at any time during the 12 months since the last tax deadline. Droughts are more likely to occur in the summer, so any-same-year drought could have occurred after many of the migration events recorded for a given tax-year took place

FIGURE 18.
Changes in Migration due to Drought Lasting Multiple Years

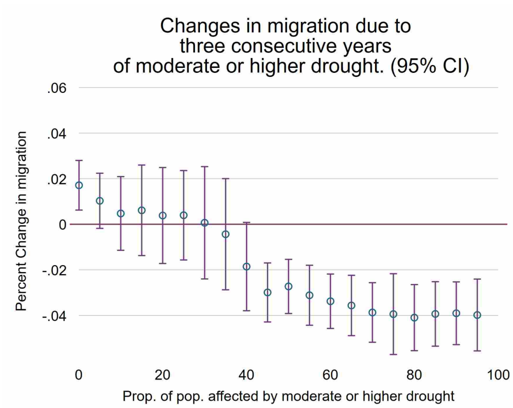
(a)



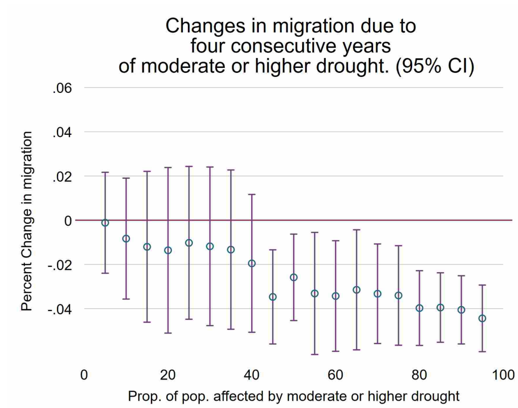
(b)



(c)



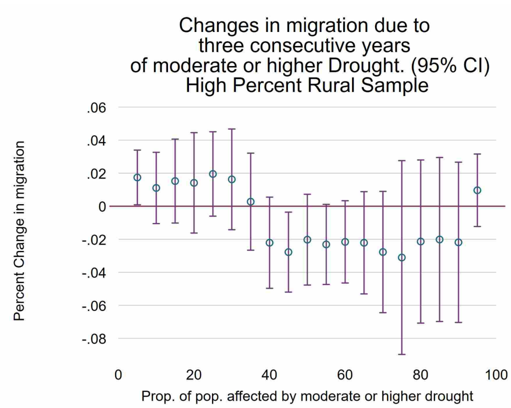
(d)



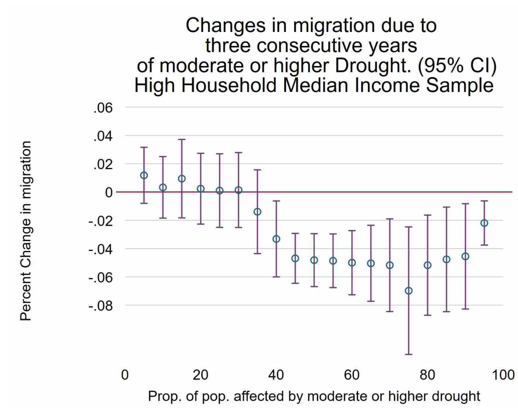
poverty, and foreign born residents have the largest reduction in out-migration as a consequence of moderate or worse drought. The coefficient estimates increase from about 2% to about 4%. These demographics are those that are associated with low income and high poverty, indicating that this effect is likely caused by liquidity constraints. Counties that are more rural, higher percentage farms, higher percent latino, higher percent black, and higher percent working age population exhibit patterns similar to those in the full sample, indicating that these variables do not change the overall pattern.

FIGURE 19.
Changes in Migration due to Drought Lasting Multiple Years. Samples Based on top 40% of Demographic in the Origin County

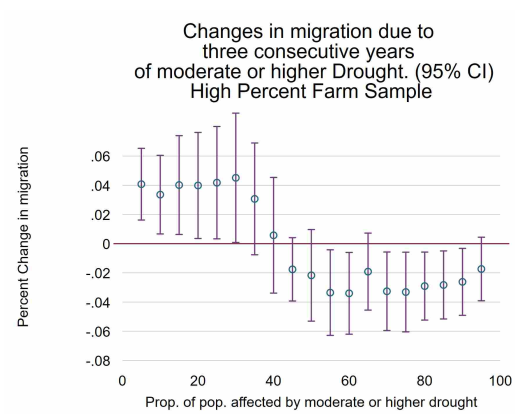
(a)



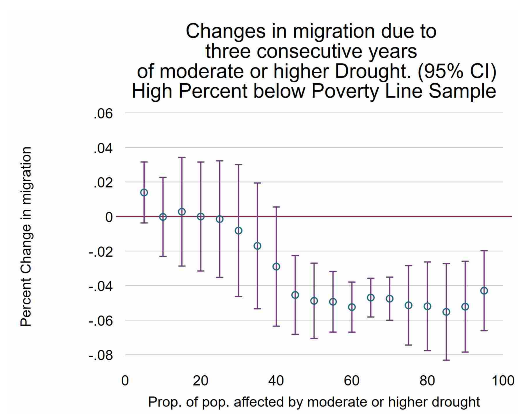
(b)

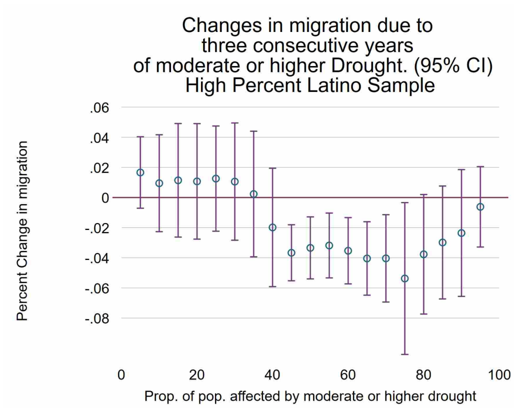


(c)

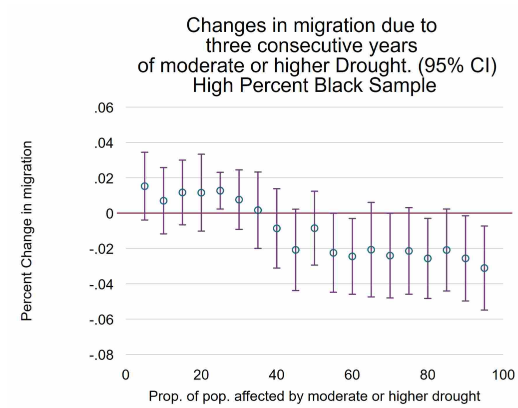


(d)

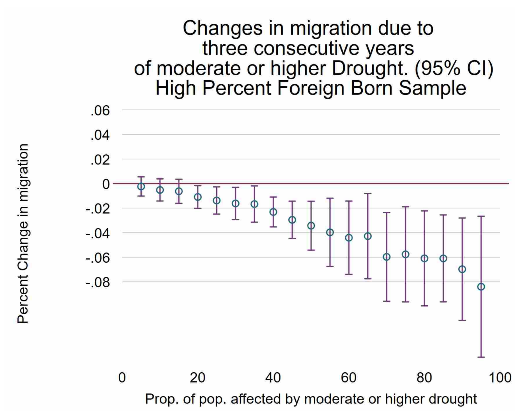



Changes in migration due to
three consecutive years
of moderate or higher Drought. (95% CI)
High Percent Latino Sample
Percent Change in migration
Prop. of pop. affected by moderate or higher drought

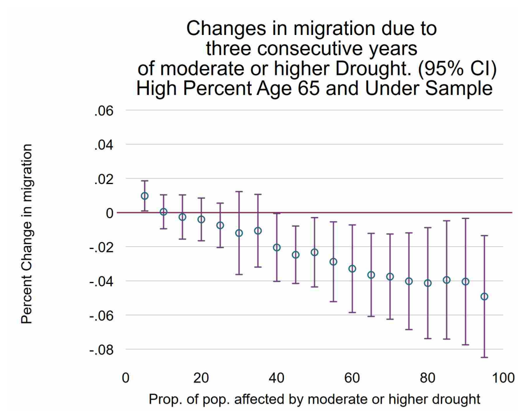
(e)


Changes in migration due to
three consecutive years
of moderate or higher Drought. (95% CI)
High Percent Black Sample
Percent Change in migration
Prop. of pop. affected by moderate or higher drought

(f)


Changes in migration due to
three consecutive years
of moderate or higher Drought. (95% CI)
High Percent Foreign Born Sample
Percent Change in migration
Prop. of pop. affected by moderate or higher drought

(g)


Changes in migration due to
three consecutive years
of moderate or higher Drought. (95% CI)
High Percent Age 65 and Under Sample
Percent Change in migration
Prop. of pop. affected by moderate or higher drought

(h)

Discussion

The results show that contemporaneous drought has a small impact on migration decisions. Many of the coefficients on the drought variables are insignificant indicating no effect. The coefficient on exceptional drought in the origin county indicates that a change from 0% of the population affected by exceptional drought to 100% affected by exceptional drought would reduce out-migration by 4% from the mean migration for that origin-destination county pair.

The estimates from the discrete drought indicator are similar in magnitude. Three consecutive years of drought reduces out-migration by 2-4% from the mean of the county pair. The 95% confidence intervals cover a range of 2-6%. This result is smaller in magnitude than the estimates from Ethiopia, Tanzania, India, and Malawi that are about 5-10 times larger (Gray and Mueller, 2012; Lewin et al., 2012; Dallmann and Millock, 2013; Kubik and Maurel, 2016).

The results for models that explore the effects of multiple-year droughts in the U.S. indicate that persistent drought appear to lock people in to their current location, rather than forcing out-migration. Theoretical models of migration do suggest that liquidity constraints could prevent people from migrating, even if the returns to migration would be positive. Modestino and Dennett (2013) and Andersson and Mayock (2014) find that migration is reduced when housing prices are lower, particularly when homeowners are "underwater" on their mortgages. This is another plausible channel for how drought could reduce out-migration in the U.S. in addition to individuals that do not have the means to migrate.[8] Future

[8]The appendix includes results when the percent of home that have their price reduced is included in the regression. The coefficients are negative for both origin and destination counties, indicating this may be a plausible channel for households reducing out-migration due to poor environmental conditions

research could explore whether drought has an influence on housing prices that could be causing this effect.

Barbier and Hochard (2018) suggest that migration could be a way to adapt to climate change by reducing the costs of climate change. They suggest that when economic activity becomes less-suited to local conditions, migration will allow individuals and industries to reoptimize by moving to the locations where utility levels or profits will be maximized under the new climate regime. These results suggest that rather than allowing climate-change costs to be mitigated through this type of adaptation, increased prevalence of drought may reduce mobility within the United States and moreso for some less-advantaged groups.

Future Research

Further analysis of this project will include creating a panel with data that is presently truncated. Including origin-destination pairs that are below the censoring threshold for some years, and using a tobit-type model will allow me to include more counties in the sample.

In addition, I will work to improve the results using cumulative drought measures. Currently the results show a range of possible cutoffs. Future versions will choose a cutoff, and then show that the results are robust to other cutoffs that are similar.

I will also include robustness checks to different ways of measuring the drought, including using seasonal or monthly indicators instead of the annual mean.

Conclusion

This paper investigates the effects of drought on migration flows in the United States. My results suggest that a single year of drought has minimal impact on migration, but that multi-year droughts seem to reduce out-migration. This reduction in geographic mobility could be due to households facing liquidity constraints and being unable or unwilling to pay the up-front moving costs. This result is stronger for origin counties that have higher poverty rates and lower incomes, indicating that low-income households are disproportionately affected. However, I do not find evidence that minority groups or more employment in agriculture are similarly affected by drought exposure.

These lesser mobilities in response to drought should be considered as climate change policy is developed and enacted. Developing optimal climate change policy requires full knowledge of the costs (and any potential benefits) and the distribution of individual net benefits across the population. Migration has been proposed as both a cost of climate change, and as a mechanism to reduce costs through adaptation. The results of this paper suggest that, at least in the United States, migration will not play a strong role in mitigating costs, and that people are likely to continue to live in areas that suffer damage. To preserve people's well-being if they remain exposed, other types of adaptation will be necessary.

Future studies could examine liquidity traps and potential mechanisms, particularly whether people are more likely to be facing income traps where they cannot afford the moving costs, or whether the causes are less direct such as loss of property value. It would also be valuable to study how drought and climate affect migration in other high-income regions such as the European Union.

Appendix

Table 13 Shows the results of the panel regression with the inclusion of percent of homes that have their price reduced in origin and destination counties. This variable is a good indicator for when the housing market is in a downturn. The coefficient is negative for both origin and destination counties. This indicates that origin counties with weaker housing markets do see reduced out-migration, and that destination counties with weaker housing markets also see less in-migration.

TABLE 13.
Changes in ln(Migration) due to Drought

	(1) Full Sample	(2) More Rural Counties	(3) Poorer Counties
Origin: Prop. pop abnormally dry	0.0000151	-0.0000667	-0.000328
	(0.000172)	(0.000165)	(0.000232)
Origin: Prop. pop mod drought	-0.000222	0.0000309	-0.000141
	(0.000167)	(0.000182)	(0.000234)
Origin: Prop. pop severe drought	0.000126	-0.0000368	-0.000223
	(0.000169)	(0.000154)	(0.000166)
Origin: Prop. pop extreme drought	-0.0000776	0.000288	0.0000595
	(0.000249)	(0.000288)	(0.000248)
Origin: Prop. pop exceptional drought	-0.000379**	-0.000576*	-0.00125***
	(0.000148)	(0.000326)	(0.000178)
Destination: Prop. pop abnormally dry	0.0000386	0.000125	0.000247
	(0.000162)	(0.000161)	(0.000213)
Destination: Prop. pop mod drought	-0.0000708	-0.000277	-0.00000302
	(0.000108)	(0.000187)	(0.000160)
Destination: Prop. pop severe drought	0.000390	0.000249	0.000725***
	(0.000258)	(0.000180)	(0.000232)
Destination: Prop. pop extreme drought	-0.00000700	-0.0000115	0.000103
	(0.000204)	(0.000239)	(0.000177)
Destination: Prop. pop exceptional drought	-0.000318	-0.0000531	0.000109
	(0.000218)	(0.000218)	(0.000226)
Origin: Percent Price Cuts	-0.00420*	-0.00459**	-0.00776***
	(0.00233)	(0.00178)	(0.00204)
Destination: Percent Price Cuts	-0.00539***	-0.00316**	-0.00359**
	(0.00146)	(0.00157)	(0.00137)
No. obs.	107865	36597	39291
FE	Orig-Dest pair	Orig-Dest pair	Orig-Dest pair
Time FE?	Yes	Yes	Yes
Clustered by:	Orig/Dest State	Orig/Dest State	Orig/Dest State

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Other control variables include flooding, hailstorms, heat waves, hurricanes, severe storms, tornadoes, wildfires, and wind storms, and severe winter weather in origin and destination counties
Omitted Categories: Origin: Prop. pop no drought and Destination: Prop. pop no drought

CHAPTER IV

DO HOUSING BUBBLES AFFECT HEDONIC PROPERTY VALUE ESTIMATES? A MONTE CARLO EXPERIMENT

Introduction

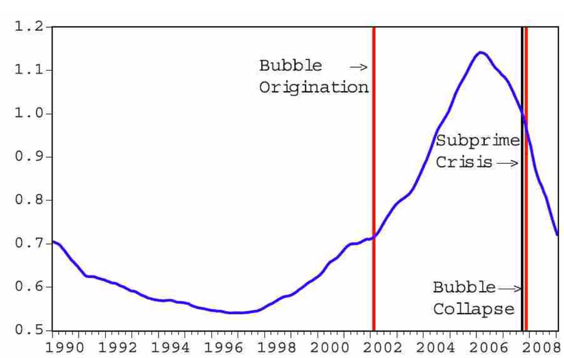
The hedonic property value model has been used since the 1970s to evaluate the benefits of environmental quality and other amenities and disamenities and local public goods. The model allows the researcher to infer how much individuals are willing to pay for marginal improvements of their neighborhoods. Hedonic property value models are ubiquitous in determining the value of clean air (Chay and Greenstone, 2005), crime (Linden and Rockoff, 2008), shale gas development (Muehlenbachs et al., 2015; Delgado et al., 2016), and EPA regulations (Mastromonaco, 2015)

In a typical hedonic regression, the logarithm of the purchase price of residential properties is regressed on the characteristics of the property. The coefficients on the independent cariables are interpreted as the implicit price of the characteristics. A key assumption in these specifications is that the purchase price of the property is its "fundamental value"; the present value of the expected future net benefits from the property over its lifetime. The expected net benefits of the property will determine the rental price. Mathematically, this assumption implies that $P_i = \sum_{t=1}^{T} \frac{rent_{it}}{(1+r)^t}$, where $rent_{it}$ is the market rental rate and P_i is the selling price of the property, and T is the expected life of the property (Phaneuf and Requate, 2017). In the presence of a bubble in the housing market, this assumption is likely to be violated, and this has not previously been studied by economists.

Intuitively, we can use the definition of bubbles suggested by Stiglitz (1990): "If the reason that the price is high today is only because investors believe that the selling price will be high tomorrow—when 'fundamental' factors do not seem to justify such a price—then a bubble exists. At least in the short run, the high price of the asset is merited, because it yields a return (capital gain plus dividend) equal to that on alternative assets"

Phillips and Yu (2011) published a seminal paper on detecting the presence of bubbles empirically. Figure 19 reproduces a figure from their paper that shows the housing price index divided by the rental price index for the United States.

FIGURE 19.
House Price Relative to Rental Price



While the ratio of selling price to rental price was relatively constant from 1990 to the early 2000s, this ratio changed drastically during the 2000s. This timing coincides with the presence of the bubble detected in their paper. Several studies in the real estate economics literature have likewise concluded that housing prices do not always represent the fundamental value of the property. Selling prices follow boom and bust trends more than rental prices, and the rental and purchase prices of properties are not cointegrated (Case et al., 1994; Gallin, 2008; Mikhed and Zemic, 2009).

The presence of bubbles is a somewhat controversial topic within economics. Many researchers are uncomfortable with bubbles as they require some amount of behavioral biases. Prior to the collapse of the housing market during 2006–2008, many economists, including former chairmen of the Federal Reserve Alan Greenspan and Ben Bernanke, believed that housing prices would stabilize. Several prominent papers written before the collapse also claimed that there was little evidence of bubble behavior (Case and Shiller, 2003; Leung, 2004; Himmelberg et al., 2005).

The presence of the bubble can cause omitted variable bias (OVB) in measurement of the first-stage hedonic price function. In general, the standard quasi-experimental technique for correcting OVB may not be sufficient. When the pricing bubble is correlated with housing attributes, the bubble may generate dynamics in housing prices that are too complex to be corrected using quasi-experimental techniques.

Using Monte Carlo techniques, I simulate a housing market that undergoes a bubble in the housing market. I thne estimate the MWTP for an environmental amenity without considering the effects of the bubble. I find that the estimate of the MWTP for the environmental amenity is biased away from zero, and that the size of this bias increases with the size of the bubble.

The housing market provides us with a useful tool for evaluating how much individuals are willing to pay for environmental amenities. Researchers can use instances where the environmental amenity differs spatially or changes temporally, and estimate how this difference in the amenity is related to differences in the rental price of a property, i.e. $MWTP = \frac{\partial rent}{\partial q}$ where q represents the amount of the environmental amenity. It is more common to use the purchase price rather than rental price as it is typically much more available for analysis (Phaneuf and Requate, 2017). When there is not a constant relationship between implicit rental rates and selling prices, as during 2002–2008, the naive assumption that $\frac{\partial P_i}{\partial q} = MWTP$ needs to be scrutinized.

After the collapse of the housing market, there has been more focus on econometric detection of the presence of bubbles both in the housing market and for other assets. New research also allows for measurement of specific attributes of these bubbles, such as the length of the bubble and the strength of the effect (Lammerding et al., 2013; Kivedal, 2013; Etienne et al., 2014).

Examples that may illustrate how the issue of bubbles can interact with the hedonic property value model can be drawn from several studies that have estimated the willingness to pay for better school districts, e.g. Black (1999), Nguyen-Hoang and Yinger (2011), and Kuminoff and Pope (2014). Some individuals pay a premium for housing so that their children may attend higher-quality schools. However, some properties in the high-quality school districts are purchased by individuals who do not have children in school, and some may not even have children. These individuals do not have any intrinsic preference for better schools. They may pay the price premium for properties in better school districts with the belief that they can sell the property in the future for an even higher premium.

Boyle et al. (2012) discuss some of the implications that a housing bubble may have for hedonic property value estimation. They warn that caution must be used in interpreting hedonic coefficients estimated from data during a housing bubble. They also provide guidance with a set of "empirical best practices," and recommend quasi-experimental techniques with time fixed effects that are interacted with the housing characteristics, to control for changes in the shape of the price function over time. However, this strategy acquiesces to the literature claiming that changes in the housing market represent changes in the fundamental values of the properties involved, rather than just to the presence of a bubble.

This paper adds to the extensive literature that has examined and critiqued the hedonic property value model. Rosen (1974) developed the basic theoretical foundation for the model. Several authors have since refined the theory, and studied how to interpret the estimated coefficients of hedonic regressions (Bartik, 1987; Ekeland et al., 2002, 2004; Yinger and Nguyen-Hoang, 2016). One of the central tenets of Rosen's theory is that the implicit price of the attributes of the homes is given by the tangent of the buyer's bid curves and the seller's offer curves. The combined envelope of these two functions defines the implicit price that can be interpreted as the MWTP for those attributes. Of course the hedonic price function need not necessarily remain the same over time. Changes to sellers' costs are expected if technology improves or the prices of inputs change, causing their offer curves to change. As time progresses, we expect income growth and changes in preferences to change buyers' bid curves, and therefore the equilibrium implicit prices will also change. However, these changes are separate from any distortions that a housing bubble may cause. There is nothing in the hedonic regression that can separately identify (1) the effects of a bubble from (2) the effects of changing implicit prices. We observe only the selling price, which includes both of these effects.

Due to this problem, this research project employs Monte Carlo techniques. In the Monte Carlo data simulation the true underlying preferences of the buyers, and the characteristics of the properties available for sale are known. This allows me to hold the bid and offer curves constant, and permit me to observe the effects of the bubble only.

Many studies have also looked at the empirical implementation of the hedonic property value model to determine the best practices for obtaining unbiased and efficient estimates, e.g. Atkinson and Crocker (1987), Taylor (2003), Chay and Greenstone (2005), and Parmeter and Pope (2012), etc. The general focus of these studies is the extent to which hedonic estimates are biased due to different types of omitted variables bias (OVB) that may be caused by unobservable features of the house or the neighborhood. Previous research has not examined if these quasi-experimental techniques correct for the presence of a bubble in the housing market.

This paper most closely follows Cropper et al. (1988) and Kuminoff et al. (2010), who use Monte Carlo experiments to determine the best functional form to use in the first-stage hedonic regression and the best use of spatial fixed effects. The key difference between their work and mine is that they assume that the observed price is the fundamental price and simulate over the hedonic parameters. My work simulates over the housing stock and buyers to define the initial hedonic parameters, and then holds these fixed. I then simulate the evolution of observed prices through a bubble-generating process. Finally, I estimate the hedonic model to verify whether the true parameters can be recovered.

To simulate data a set of properties to be sold and the sales price of an equal number of households buying. I adapt the algorithm used in Kuminoff and

Jarrah (2010). Their algorithm first samples the housing stock from a database of properties in a single market. It then generates individuals with preferences drawn from known distributions and having demographics based on data from the same area where the properties in the database are located. Then a second-price bidding auction is conducted to assign each individual to a property. It is assumed that individuals cannot change the characteristics of the house (either the environmental amenity or the house characteristics), they merely purchase from the stock that is available.[1]

After the fundamental prices are generated, the prices go through the simulation of an asset pricing bubble. Thebubble generation process is explained in detail below. The bubble expands, and may suddenly contract. Home purchasers may assign some probability to the collapse of the bubble, but do not know when the collapse will occur.

After the Monte Carlo data have been generated, estimation proceeds using the standard hedonic property value model:

$$ln(P_i) = x_i\beta + \theta q_i + \varepsilon_i$$

where x_i is a vector of characteristics of the property (number of bedrooms, number of bathrooms, lot size, square footage, etc.) and q_i is the neighborhood amenity of interest. The measured parameter of interest, θ, can then be compared to the true hedonic property value function underlying the Monte Carlo data-generation process.

[1] In the long run, individuals can improve or build on their property. If they are doing so because they are expecting the standard return on investment, this will meet equation (4) in the long run. If they are doing so because they are expecting the high returns of a bubble, then their behavior will violate equation (4)

To identify cleanly parameters such as θ two commonly used quasi-experimental techniques are employed: (1) a border discontinuity model, where q changes discretely at a known geographic boundary (Black, 1999; Nguyen-Hoang and Yinger, 2011; Kuminoff and Pope, 2014) and (2) a difference-in-differences scenario where q changes exogenously at some point in time for a subset of the homes in the dataset (Chay and Greenstone, 2005). This project assesses the potential validity of many hedonic studies that have been undertaken using data collected during the 1990s and 2000s. It also gives guidance for upcoming studies during inevitable future housing booms and bubbles.

Theory

Theory of Bubbles

To model price bubbles in the housing market, I use what is known as the concept of "a rational bubble." This theory of bubble behavior is derived from Evans (1991), Campbell et al. (1997) and Phillips and Yu (2011). This type of bubble allows for explosive behavior in the price of an asset, but requires that the explosive behavior is temporary. The advantage of this type of bubble model is that it can reflect what we observe in the housing market, namely standard asset appreciation, followed by explosive behavior for a period of time, and then a collapse where the price reverts back roughly to its fundamental level. The asymptotic theory of this type of bubble formation is developed in Phillips and Magdalinos (2005) and has been shown to have the econometric properties necessary for inference. In general, the real price of a generic financial asset can be separated into two terms, the market-fundamentals term, F_t, and a bubble term,

B_t:

$$P_t = F_t + B_t \tag{4.1}$$

$$\text{where } F_t = \sum_{j=1}^{\infty}(1+r)^{-j}\mathbb{E}_t d_{t+j} \tag{4.2}$$

where d_t represents the real dividend paid to the owner of the asset and r is the interest rate. For the housing market, the dividend is the implicit rental price of the home.

The bubble term is be a rational bubble if it satisfies

$$B_t = (1+r)^{-1}\mathbb{E}_t B_{t+1} \tag{4.3}$$

where B_t, the bubble component of the observed price, is a random variable. For many applications, it is assumed that $B_t = 0$, and thus that $B_{t+j} = 0$ for all j. If this is the case, then the price of the asset is always just F_t. For standard hedonic property value models, this is the usual assumption.

The dividend paid to a property owner is the rental price of the property. For a home that is occupied by the owner, the dividend is the opportunity cost incurred by not renting the property to someone else and not having to rent a different home themselves. With no bubble,

$$P_i = F_i = \sum_{t=1}^{T}\frac{rent_{it}}{(1+r)^t} \tag{4.4}$$

The implicit rental rate for the property ise determined simply by the value of the land, the house and the usual local amenities. Estimation employs the regression equation:

$$log(P_{it}) = x_{it}\beta + \theta q_{it} + \varepsilon_{it} \tag{4.5}$$

When broadly defined, there can be many types of bubbles. For housing markets, the most relevant class of bubbles consists of those which are always nonnegative and periodically collapse. We do not tend to observe housing prices that fall below their fundamental value, except possibly under extremely rare circumstances such as in select locations for a brief time in 2008. In general, we observe bubbles that expand, and then suddenly collapse, correcting prices back to their fundamental value.

One simple way to model a bubble is to use:

$$B_{t+1} = (1+r)B_t u_{t+1} \tag{4.6}$$

where u_t is an exogenous, strictly positive, and i.i.d. random variable with $\mathbb{E}_t u_t = 1$. The bubble grows at mean rate $1+r$ indefinitely. Equation (3) represents the agents' forward-looking expectations. Agents are willing to purchase an asset in a bubble as long as the bubble grows at the standard interest rate. Equation (6) is the simplest way to generate a time series of a bubble that satisfies equation (3).

For this process, B_t will always be greater than zero. However, this bubble will not collapse. It is unlikely that a bubble that does not collapse (after growing to a high level) can exist in practice. A second condition can be added to the model to allow for collapse, and also to allow for a period of explosive growth. Assume that there is some threshold bubble size α, and that:

$$B_{t+1} = (1+r)B_t u_{t+1} \qquad \text{if } B_t \leq \alpha \tag{4.7}$$

$$B_{t+1} = [\delta + \frac{1}{\pi}(1+r)\theta_{t+1}(B_t - \frac{\delta}{1+r})]u_{t+1} \qquad \text{if } B_t > \alpha \tag{4.8}$$

Intuitively, the bubble grows at the standard interest rate, $(1 + r)$, for a period of time. Equation (7) describes this phase of the bubble. Eventually, the size of the bubble reaches the threshold level of α, and the bubble then enters an explosive phase. During the explosive phase, the bubble grows at a markedly faster rate, $(1+r)\pi^{-1}$. Equation (8) represents the explosive phase of the bubble. At each period during the explosive phase, the bubble can collapse with probability $1 - \pi$. The parameter θ_{t+1} takes a value 0 if the bubble collapses and a value of 1 as long as it does not. If the bubble collapses, B_{t+1} returns to a mean value δ. As long as $\delta u_{t+1} < \alpha$ it evolves according to equation (7) and begin the process again (Evans, 1991).

This process is classified as a rational bubble because the increased returns during the explosive phase are balanced by the chance of collapse, and equation (3) is satisfied. When the bubble collapses, the bubble will revert to value δ, and prices will return close to their fundamental level. As long as $\delta > 0$, then $B_t \geq 0$ for all t. As a consequence:

$$P_t = F_t + B_t \geq F_t \tag{4.9}$$

Hedonic Estimation in the Presence of a Bubble

Many economists have studied bubbles and their implications in asset prices. However, there is no work, to my knowledge, that incorporates bubbles in a housing market into a hedonic property value model. This section outlines some things to expect when combining bubbles and hedonic property estimation.

In the absence of any bubble, $B_t = 0$, assume that a regression that would give unbiased estimates of the marginal willingness to pay for a given amenity, θ, is:

$$F_{it} = \alpha + x_{it}\beta + \theta q_{it} + \varepsilon_{it} \tag{4.10}$$

The true MWTP of the amenity is $\frac{\partial F_{it}}{\partial q} = \theta$. When we observe data on property sales, however, we observe P_{it}, when what we truly desire as the dependent variable is fundamental home value, F_{it}.

To set up the bubble, we assume that B_{it} will be greater than or equal to zero at all times, so there must exist some number $c_t \geq 1$ such that

$$P_{it} = c_t F_{it} \tag{4.11}$$

where c_t can be viewed as the proportion by which property prices are above their fundamental value at any instant in time on average.[2] The bubble is created by dynamics that are additive in nature, as outlined in the previous section. This multiplicative factor c_t, is useful to consider for providing some insight into what to expect from the regressions. When the bubble has expanded, c_t will be high, and if there is no bubble c_t will equal 1. The general hedonic regression using cross-sectional data is:

$$F_i = \alpha + x_i\beta + \theta q_i + \varepsilon_i \tag{4.12}$$

The time subscripts have been dropped for clarity, so equation (12) represent data collected for only a single time period. We cannot observe F_i, but can observe the proxy $P_i = c_t F_i$, so we run the regression:

$$P_i = \alpha^* + x_i\beta^* + \theta^* q_i + \varepsilon_i^* \tag{4.13}$$

[2]Since $c_t F_{it} = F_{it} + B_{it}$, then $c_t \equiv 1 + \frac{B_{it}}{F_{it}}$.

which is equivalent to:

$$c_t F_i = \alpha^* + x_i\beta^* + \theta^* q_i + \varepsilon_i^* \tag{4.14}$$

If we estimate equation (12) and equation (14), the coefficients would be:

$$\theta^* = c_t\theta \quad \text{and} \quad \beta^* = c_t\beta \quad \text{and} \quad \alpha^* = c_t\alpha \quad \text{and} \quad \varepsilon_i^* = c_t\varepsilon_i \tag{4.15}$$

If we estimate a hedonic property model with data from a single time period via simple OLS, we would expect to bias our estimates by whatever proportion the home value is above its fundamental level at that given moment. We would expect to see this bias in both the estimates for the marginal value of the public good that is the target of the study, as well as the estimates of all the marginal values of the usual housing characteristics. If we naively interpret $\frac{\partial P_{it}}{\partial q}$ as the marginal price, then we will overstate the true value by the factor c_t.

More typically, the hedonic property value model is estimated using ln(Price) as the dependent variable, to reduce the heteroscedasticity in the errors. Suppose that the regression equation for cross–sectional data that would give the true parameters is:

$$ln(F_i) = \alpha + x_i\beta + \theta q_i + \varepsilon_i \tag{4.16}$$

The marginal value for the amenity is still $\frac{\partial F_i}{\partial q} = \theta$. Exponentiating both sides of this equation and then taking the derivative of F_i with respect to q_i yields:

$$F_i = e^{\alpha + x_i\beta + \theta q_i + \varepsilon_i} \tag{4.17}$$

$$MWTP = \frac{\partial F_i}{\partial q} = \theta e^{\alpha + x_i\beta + \theta q_i + \varepsilon_i} = \theta F_i \tag{4.18}$$

But suppose we instead use the observed selling price in the regression, $P_i = c_t F_i$. Taking the log of the selling price yields:

$$ln(P_i) = ln(c_t F_i) = ln(c_t) + ln(F_i) \tag{4.19}$$

Given that we have assumed $c_t \geq 1$, it should be the case that $ln(c_t) \geq 0$. If we let $ln(c_t) = \kappa_t$ and consider the regression that uses P_i in place of F_i,

$$\kappa_t + ln(F_i) = ln(P_i) = \alpha^* + x_i\beta^* + \theta^* q_i + \varepsilon_i^* \tag{4.20}$$

the estimated coefficients from equation (20) compared to the true estimates from equation (16) are:

$$\theta^* = \theta \quad \text{and} \quad \beta^* = \beta \quad \text{and} \quad \alpha^* = \kappa_t + \alpha \tag{4.21}$$

it may seem that there is no bias with the regression in equation (20) since $\theta^* = \theta$. However, the ultimate goal of hedonic studies is to determine the MWTP of the public for an environmental amenity. When we use P_i as a measure of property value instead of F_i, equation (18) becomes

$$MWTP = \theta P_i = \theta c_t F_i \tag{4.22}$$

If the model is estimated in semi-log form, the estimated MWTP is biased by the same amount as when it is estimated in level form. We interpret these coefficients as percent differences in property price for a one-unit increase in q_i. The same θ coefficient in a model with property sales inclusive of a bubble will be interpreted as implying a larger marginal value. This yields the same bias, namely that the estimated MWTP for one unit of amenity q_i is biased by a factor equal to the proportion by which property prices lie above their fundamental levels.

I examine two specifications that are commonly used in hedonic property value models, a border discontinuity model and a difference-in-differences model. We expect that the border discontinuity simulation exhibit the bias highlighted here. It is less clear how the theory manifests itself in the difference-in-differences model that uses longitudinal or panel data.[3] As the bubble expands or collapses over time, c_t is also changing with time. Monte Carlo simulation allows me to estimate the impact of the bubble in a more complex model.

Data

The data for this analysis are generated using a modified version of the algorithm presented in Kuminoff and Jarrah (2010).[4] Their algorithm takes an equal number of households and homes as inputs, and as output, assigns each household to exactly one property. Each household maximizes its utility over preferences for the characteristics of the house, the presence of the public good, and over their other consumption.

In Kuminoff and Jarrah, each household i has utility for property j given by:

$$U_{ij} = ln(y_i - P_{ij}) + \alpha_i ln(x_j) + \lambda_i ln(q_j) \tag{4.23}$$

[3]One technique used to account for OVB is to only use resale data on properties that have sold multiple times. Future work could check the performance of this model when one (or both) of the transactions occur during a bubble.

[4]The central feature of this algorithm is that it will take a set of property prices and property characteristics and calibrate the household preferences. After this calibration it can create a new set of selling prices after a shock to the market, or for a new set of property characteristics.

i.e. y_i is the income of household i. Parameters α_i and λ_i are the household-specific preferences over the dwelling and lot characteristics and the public good, respectively.

The algorithm conducts a second-price bidding auction to assign each property to a buyer.[5] Each household submits a bid for every property based on their income and their preferences over property amenities. The household with the highest bid wins the auction and pays the second-highest price for the property. Kuminoff and Jarrah show that the algorithm converges to an equilibrium that assigns one household to one property.

The set of properties for this analysis come from property sales in the San Francisco Bay area from 1993 to 2008. The characteristics of each property are drawn from actual sales. The assignment of the level of the public good is done as part of the simulation process, and will be described in more detail in the results section. The selling price is modified by adding a bubble over time.

The ideal method to introduce the bubble would be to change the households' expectations of the future selling price of the property. As the bubble begins to form, households observe the increased returns, and are willing to pay a higher portion of their income for property in anticipation of receiving a higher selling price in the future. However, the algorithm as it stands requires approximately one week to converge. Adding a value-function calculation for each household at each step would increase the run-time beyond present computational capacity. Instead, the algorithm determines the initial price with no bubble

[5] A second-price auction is used because the optimal strategy in the Nash Equilibrium is for each individual to bid their valuation. In a first-price auction, the optimal strategy for the individual with the highest bid is to bid the second-highest individual's valuation + ε and not their own valuation (Mas-Colell et al., 1995).

present, and then the bubble will be permitted to expand exogenously using equations (7) and (8) from the theory section.

As above, the observed selling price is the sum of the fundamental component and a bubble component:

$$P_t = F_t + B_t \tag{4.24}$$

The algorithm above determines F_t. I then incorporate a second process that changes the price over time by adding a bubble term. To do this, an initial value of B_t must be assigned. The simplest choice would be to assign a constant number that is the same for all properties. However, this would imply that low-cost properties derive a larger proportion of their price from the bubble. Kuminoff and Pope (2013) show that observations of actual housing markets show similar overall percentage growth across all segments of the housing market. As a consequence, the initial value for the bubble is chosen as a fixed percentage of the fundamental price of the property. I use $B_0 = 0.05F_t$ for each property in the sample, with a sensitivity analysis concerning this arbitrary setting.

Results

Border Discontinuity Model

One common method for conducting a hedonic property value study is to collect cross-sectional data in a single housing market that spans a geographical border between jurisdictions with different amenity levels, and to use a border discontinuity model to identify the value of the amenity. The border discontinuity design allows the researcher to minimize OVB due to unobservable neighborhood characteristics. This model is commonly used to estimate the value of school quality, e.g. (Black, 1999; Nguyen-Hoang and Yinger, 2011; Kuminoff and Pope, 2014). School districts cover relatively large areas, so simply comparing property values in the higher-quality school district to those in the lower-quality school district captures the value of the school system itself, but also capture other features that are correlated with school quality. In general, higher-quality schools tend to be in better neighborhoods. To correct for this problem, the border discontinuity model compares only those homes that are close to the district boundaries, where the changes in the other unobserved neighborhood features will be small. For estimation, this requires either adding a set of dummy variables for properties that are on the boundary (or adding a variable that measures distance from the boundary), and a set of dummies for properties that are in the higher-quality school district. The general regression equation in semi-log form is:

$$ln(P_i) = x_i'\beta + \gamma B_i + \theta^{RD} D_i + \eta_i + \varepsilon_i \tag{4.25}$$

where the x_i are the standard observable features of the property (including an intercept), η_i is a set of county or neighborhood fixed effects, B_i is the set of dummies for all properties that are on either side of the boundary. D_i is an indicator variable that =1 if the property is located in the high-quality school district (i.e. receives the public good) and $D_i = 0$ elsewhere.

My simulation generates property price data for 20 years. The bubble is assigned ten years of non-explosive growth (Eq 7), and then given 10 years of explosive growth (Eq 8). Estimation is then undertaken using two separate cross sections. The value of the public good is calculated in year 1, when the bubble has just a small effect. The implied value of public good is also calculated in year

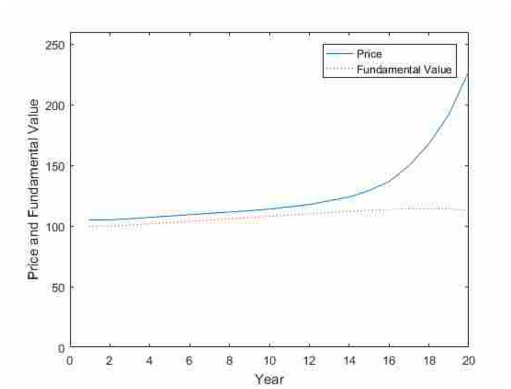
TABLE 14.
Percent bias in hedonic estimate of MWTP for public good with border discontinuity model (means and standard deviation from 300 Monte Carlo replications)

	$\pi = 0.65$		$\pi = 0.75$	
	Linear	Semi-Log	Linear	Semi-Log
Year 1 (No Bubble)	0.049 (0)	-0.025 (0)	-0.11 (0)	-0.03 (0)
Year 15	0.34 (0.057)	0.24 (0.053)	0.09 (0.027)	0.20 (0.029)
Year 20	1.06 (0.56)	0.91 (0.53)	0.27 (0.013)	0.39 (0.014)

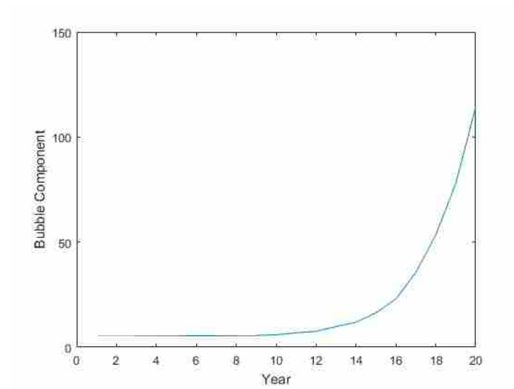
20, after the bubble has had time to go through its phase of explosive expansion. Households' true preferences over the public good are positive, but do not change with time. For the simulation $B_0 = \delta = 0.05F_t$, $r = 0.01$, $u_t \sim logN(1, 0.005)$ and π is given two different values of 0.65 and 0.75. Each simulation involves 300 replications.

With this type of bubble-generating process, some size of bubble is always present. During the 10 years of non-explosive growth, the bubble is still present at 5% of the fundamental value. We can interpret this phase as the housing market behaving normally with no bubble present. With this model for bubble behavior, the initial value of the bubble must be large enough that when explosive growth occurs, the bubble portion is a significant contributor to the price. The values of π of 0.65 and 0.75 are used because, on average, (in year 20), the observed selling price ise 100% and 50% above the fundamental price, respectively. Figure 2 shows the time paths of the bubble that is generated, as well as the fundamental value of the properties and the resulting prices.

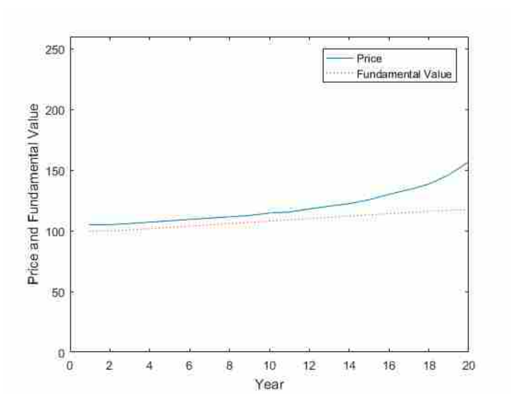
The true property values to which naive estimates are compared, are given by the results of the first-stage simulation. For the linear specification, this is $\frac{\partial F}{\partial q} = \theta$, where F is the output from the first stage of the simulation, and for the semi-log specification, this is θF_{it}. The true values of θ and θF_{it} are compared in Table 14 to the naively estimated values of parameters $\widehat{\theta}$ and $\widehat{\theta} P_{it}$.



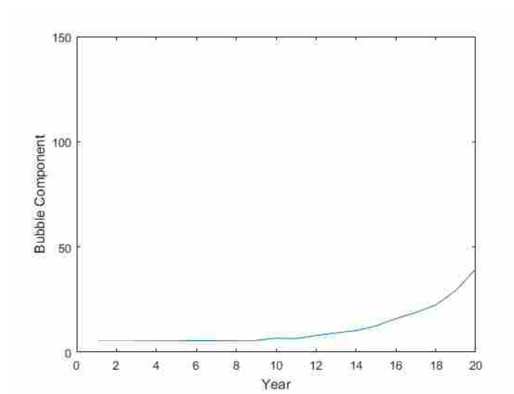
(a) $\pi = 0.65$



(b) Bubble Portion



(c) $\pi = 0.75$



(d) Bubble Portion

FIGURE 20.
Prices, Fundamental Value, and Bubble Portion for Example Simulation

In the first year, the naive estimates show minimal bias, with the semi-log specification performing better than the linear specification. This confirms prior Monte Carlo results (Cropper et al., 1988; Kuminoff et al., 2010).

The bias in the naive estimates of the key coefficients is significant in the estimates based on data in years 15 and 20 when the housing market is in the midst of an explosive bubble. These results are dependent on the size of the bubble compared to fundamental value at the time transaction prices are measured. As the bubble expands, housing prices move farther away from their fundamental values. The bias from year 15 is smaller than the bias in year 20 when the bubble has expanded further. For $\pi = 0.65$, property prices are, on average, 100% above their fundamental values at the end of year 20. The bias recovered is similar to this value. The results are analogous for $\pi = 0.75$. The bubble does not expand as quickly with the higher value for π, but the bias in the naive estimates is near to the proportional difference between the fundamental value and the observed price. If the bubble collapses and prices return to their fundamental values, then the bias will no longer be present.

Due to the nature of the cross-sectional data used in the border discontinuity model, when the usual hedonic property value model is used for applied empirical studies, the available data cannot tell us whether the housing market is in a bubble. If a researcher wishes to correct for the presence of a bubble, it is necessary to look at a time series of aggregated data for that housing market, and to test for the presence of the bubble using the methods outlined in Phillips and Yu (2011). After determining the timing and size of the bubble, then the prices could be deflated by the estimated amount to recover the fundamental property values.

Quasi-experimental Model

The second simulation uses a naive generalized difference-in-differences model to estimate the value of a change in the public good. This section follows the standard assumptions of a quasi-experiment. There is a treatment group that receives a plausibly exogenous change in the public good at some time t, while the control group experiences no change in the public good.

This regression uses the equation:

$$lnP_{it} = x'_{it}\beta + \gamma_1 D_{it} + \gamma_2 T_{it} + \theta^{DD} \times T_{it} \times S_{it} + \eta_i + \varepsilon_{it} \tag{4.26}$$

i.e. where D_{it} is an indicator variable for the properties that receive the public good, T_{it} is a time indicator for the sale occurring after the treatment, and the η_i are county or home fixed effects. For the model with time fixed effects, the post-treatment dummy is replaced with a set of time fixed effects and the regression equation becomes:

$$lnP_{it} = x'_{it}\beta + \gamma_1 D_{it} + \theta^{DD} \times T_{it} \times D_{it} + \mu_t + \eta_i + \varepsilon_{it} \tag{4.27}$$

For this exercise, the bubble is simulated analogously to the previous section, where the bubble exhibits a non-explosive phase for 10 years, and then an explosive phase for 10 years. The simulation parameters are also the same, $B_0 = \delta = 0.05F_t$, $r = 0.01$, $u_t \sim logN(1, 0.005)$, and $\pi = 0.75$ and $\pi = 0.65$. This simulation gives insight into the bias that may be present if naive hedonic property value methods are employed with data from the 1990s and 2000s up until 2006 (i.e. prior to the crash of the housing market). The value of q changes from 0 to 1 for the treatment group in year 15.

TABLE 15.
Percent bias in hedonic estimate of MWTP for public good with border discontinuity model
(means and standard deviation from 300 Monte Carlo replications)

	$\pi = 0.65$		$\pi = 0.75$	
	Linear	Semi-log	Linear	Semi-log
Difference in difference	0.22 (0.29)	0.50 (0.022)	0.0627 (0.22)	0.223 (0.010)
Difference in difference with time fixed effects	0.17 (0.28)	0.46 (0.017)	0.0428 (0.21)	0.204 (0.008)
Difference in difference with house fixed effects	0.18 (0.37)	0.48 (0.018)	0.0435 (0.22)	0.208 (0.009)

The results in Table 15 show that the use of quasi-experimental methods does not completely remove the bias caused by the bubble. Comparing the extent of the bias reported in Table 2 to the bias reported in the previous section, note that the bias is about one-third as large for the linear specification, and half as large for the semi-log specification, compared to the border discontinuity model. The estimates are very similar regardless of whether home fixed effects are used and a resale only model is used such as that in Bajari et al. (2012). The resale only model corrects for endogeneity in the home price that is due to unobservable attributes of the home or neighborhood, but it is unable to correct for a bubble that affects the entire housing market. Comparing the two model specifications, the linear specification does not display as large a bias, but the linear model estimates are noisier than those from the semi-log specification.

Future Research

There are several directions in which further analysis could proceed. The first issue is that this research demonstrates how bubbles in the housing market can cause bias in the estimates of MWTP for environmental amenities or other public goods. However, the analysis does not yet offer a clear solution or a new "best practice" for how to correct this problem so as to obtain unbiased estimates from observational data.

One significant hurdle to obtaining unbiased estimates is that there is no direct way to measure the fundamental price of housing. There may be other variables that can be included in the dataset that could carry information on the size of the bubble. Additional research could undertake to determine whether data from a different housing market, not in a bubble, or some other variable(s) could be used to instrument for (or be included in) the regression to reduce or remove the bias.

Another potential source of insight for hedonic property value models is to apply some of the techniques developed by researchers studying bubble formation and evolution in financial markets. It is standard practice in the hedonic property model to deflate prices by CPI to obtain real property prices rather than nominal prices. It may be possible to construct an index representing the strength of the bubble at each point in time. Deflating prices with this index could give a better measure of fundamental prices to use as the dependent variable. A problem with this potential solution is that the housing bubble of the 2000s was heterogeneous across different locations. Further research is thus needed to determine if the measurement error from estimating the index in a single market would outweigh the gains of such an index.

Finally, it may be possible to create a dynamic price simulator where the bubble is produced endogenously. Branch and Evans (2011) have shown that agents using "least squares learning" can create asset-pricing bubbles that first grow and then collapse. Using such a model might make it possible to produce a time-series of housing prices in one step, instead of having to rely on the two-step simulator used in this paper. A Branch-Evans type of model could also be calibrated to actual data. Using a structural model, it may be possible to estimate what proportion of the observed price changes are due to bubbles and what proportion are due to changes in preferences or technology. Using this approach, it may be possible to reestimate the total and marginal WTP for properties and their amenities obtained from papers that have been produced using data across time periods that overlapped with the recent housing price bubble.

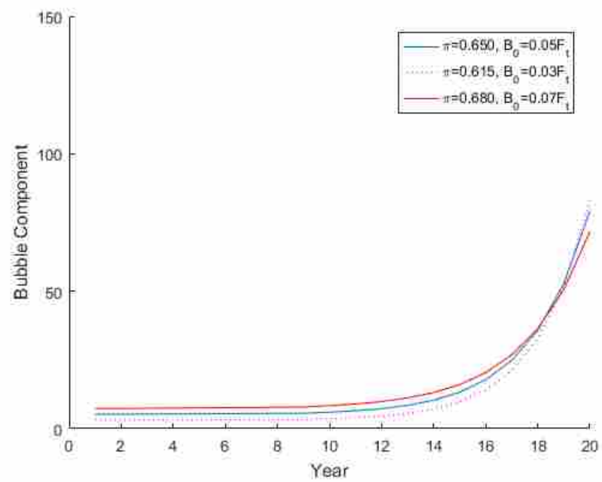
Conclusion

This paper conducts a Monte Carlo study to determine the extent of the bias of the key parameters of a naive hedonic property value model caused by the presence of a bubble in the housing market. I leverage the ability of a Monte Carlo study to hold the fundamental hedonic price function constant, and control for all other omitted variables while prices experience an explosive bubble.

The results show that the presence of a bubble does bias the estimates for the MWTP for public goods obtained via a naive hedonic regression, and that the size of the bias is proportional to the magnitude of the bubble. The two most common techniques for removing typical omitted variable biases—border discontinuity models, and difference-in-differences models—do not fully correct for the bias, although the difference-in-differences model appears to produce less biased estimates than the border discontinuity model.

These results suggest that researchers should consider the presence of bubbles in the housing market, particularly when conducting hedonic studies that use data from the 2000s. Previous studies have shown that ignoring changes in preferences, income or information can bias estimates of MWTP for environmental amenities (Kuminoff et al., 2010; Boyle et al., 2012). The research described in this paper shows that we should also consider changes to the housing market that are based on bubble behavior. If we erroneously interpret bubble behavior as fundamental changes in housing preferences, we will come to misleading conclusions when evaluating environmental amenities. If these estimates are used for policy, the exaggeration of the value of some environmental amenities could lead to suboptimal policy choices. Future work is necessary to determine the best

FIGURE 21.
Comparison for different bubble parameters



modeling techniques to correct for bubble-induced biases in hedonic property value models.

Appendix A: Sensitivity Analysis

This section examines the sensitivity of the results to changes in the parameters that create the bubble dynamics. In the paper, the parameters chosen were $\delta = B_0 = 0.05F_i$ and two different values for π, 0.65 and 0.75 for the explosive phase of the bubble. This section examines the effects of changing these parameters.

Changing only one parameter will create changes in the bubble dynamics. Lowering π makes the bubble more explosive, and lowering $\delta = B_0$ would lower the bubble across the whole time series. To create a bubble with similar dynamics as those used in the paper, the two parameters δ and π can to be changed in tandem. Figure 21 shows an example plot for three different scenarios that produce a

TABLE 16.
Percent bias in hedonic estimate of MWTP for public good with border discontinuity model for different model parameters

	$\pi = 0.65, B_0 = 0.05F_t$		$\pi = 0.615, B_0 = 0.03F_t$		$\pi = 0.680, B_0 = 0.07F_t$	
	Linear	Semi-Log	Linear	Semi-Log	Linear	Semi-Log
Year 1 (No Bubble)	0.049 (0)	-0.025 (0)	0.049 (0)	-0.025 (0)	0.049 (0)	-0.025 (0)
Year 15	0.34 (0.057)	0.24 (0.053)	0.33 (0.048)	0.23 (0.042)	0.29 (0.058)	0.22 (0.055)
Year 20	1.06 (0.56)	0.91 (0.53)	1.19 (0.61)	0.99 (0.54)	0.94 (0.44)	0.89 (0.47)

bubble similar to $\pi = 0.65$ and $B_0 = 0.05F_t$. If the simulation were to be extended across more time periods, a bubble with a higher value of π (and lower δ) would expand faster and overtake the other bubbles. These value show reasonable similarity for the 20 years that are considered. There is a trade-off in deciding values for the parameters. Lower values of δ allow for property values that are closer to the fundamental value when the bubble is not in its explosive phase. However, these lower values for δ require a smaller value of π to generate the same size bubble. Smaller values of π create more explosive growth rates during the explosive phase, and there are practical considerations regarding how fast a bubble could expand in practice.

The results in Table 16 show that changing the parameter values creates some minor changes to the magnitude of the recovered estimates. Small differences are expected as changing the parameters does cause small changes in the dynamics of the bubble. However, the central theme of the results is still the same: we do not see the results vanish, or any changes in signs of the coefficients.

CHAPTER V

CONCLUSION

This dissertation examines how drought and water shortages influence society and also studies the validity the hedonic property value model when there is a bubble present in the housing market. Chapter II focuses on how drought influences crime in the context of South Africa, a middle-income country. Chapter III focuses on how drought influences migration within the United States, and Chaper IV examines how estimating hedonic property value estimates of the MWTP for environmental amenities may be biased when there is a bubble present in the housing market.

The analysis described in these three chapters can help to advise policy makers who are considering public policy that affects water planning and conservation, or any analysis that uses the hedonic property value model to estimate the value of an environmental amenity or disamenity. The research documented here can also be used as part of an analysis of climate change policy, where the potential costs due to water shortages and drought can be fully considered.

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