Credit Access and Housing Insecurity: Evidence from Winter Utility Shutoff Protections

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Abstract

Fifty-six percent of urban renters face some level of housing insecurity. I explore the role of credit access, or lack thereof, as a contributing factor. To do so, I study a temporary line of credit extended to households in the form of protection from heat shutoffs during the winter. These protections allow households to delay winter energy payments without risk of losing their heat. I adopt a triple difference-in-differences (DDD) approach, leveraging variation in states' shutoff protection dates and census tracts' average energy burdens. I estimate that the temporary extension of credit reduces the eviction filing rate by 4% in census tracts with high energy burdens. I provide suggestive evidence that eviction filings do not spike after the temporary credit access ends, implying a net negative effect of temporary credit access on filings over the entire year. I further demonstrate that a 3% increase in rental payments explains the decline in eviction filings, which is consistent with access to credit allowing renters to smooth consumption.

Keywords: Eviction, rent, credit access, credit constraints, housing insecurity, energy burden

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1 Introduction

Landlords file an average of 3.6 million eviction cases annually in the U.S. (Gromis et al. 2022). These filings are costly to renters, generating a harmful public record and risk of displacement. Among tenants named in an eviction filing, credit constraints appear to play a role. Despite often owing as little as one month of rent at the time of the filing (Badger 2019), these tenants appear to have insufficient credit to avoid an eviction filing (Collinson et al. 2022). While existing work documents the effects of wages (Agarwal et al. 2022) and health insurance coverage (Gallagher et al. 2019; Zewde et al. 2019) on housing insecurity, no known causal evidence exists on credit access as a potential driver.

Understanding whether access to credit affects housing insecurity is a key policy question for designing optimal housing assistance. Most federal housing assistance programs available to renters, such as vouchers and public housing, lower the cost of housing but do not directly address credit constraints nor reach the majority of assistance-eligible households (Joint Center for Housing Studies 2013). To investigate the role of credit constraints, I examine an understudied set of policies that provide access to small amounts of credit: winter utility shutoff protections. These state policies limit public utilities from disconnecting residential electricity or gas due to non-payment during the winter months. While winter energy bills accrued during protected periods are not forgiven, households can forego payment during this time without risk of disconnection. Acting as a temporary line of credit, these protections offer a unique setting to study the role of credit access for housing-insecure populations.

In studying the effects of winter utility shutoff protections, I focus on families who have the potential to benefit from temporary access to relatively small amounts of credit—families facing high credit constraints and energy burdens.[1] Since credit-constrained renters near the margin of an eviction filing have a strong incentive to pay rent to avoid a filing, I hypothesize that winter utility shutoff protections enable vulnerable renters to shift resources away from utility bills and toward rental payments, reducing eviction filings. This hypothesis is supported by interviews with low-income renters in Milwaukee and Boston that suggest that renters allow heating bills to pile up in the winter and instead prioritize rental payments (Desmond 2016; Halpern-Meekin et al. 2015). Some renters also report utilizing EITC payments or other tax refunds to catch up on utility bills before the shutoff protections end in the spring (Sykes et al. 2015).

I test whether places with high average energy burdens experience a change in the rate of eviction filings during periods with winter shutoff protections. Any temperature trends in eviction filings could confound estimates of the effect of shutoff protections. I address

[1] Energy burden is defined as the ratio of energy costs to household income.

endogeneity concerns about temperature by exploiting within-state variation in the average energy burdens of census tracts. However, low energy burden areas may provide poor control trends in eviction filings for high energy burden areas. I address this endogeneity concern by exploiting across-state variation in the timing of winter protections. With these sources of variation, I estimate a triple difference-in-differences (DDD) specification. This approach allows me to control for time-invariant characteristics of census tracts, state-wide weekly trends in eviction filings (which includes temperature trends), and differential weekly trends in eviction filings for high and low energy burden areas.

I find that winter utility shutoff protections lead to 9.7 fewer eviction filings per 100,000 renter-occupied households in census tracts with high average energy burdens. This effect is equivalent to a 4% decline in the eviction filing rate relative to unprotected periods of the year in high energy burden areas. I find no evidence of any spike in filings after the protections end in the spring, which suggests that the temporary credit access does not simply delay eviction filings. I further demonstrate that the decline in eviction filings attributed to winter utility shutoff protections is driven by increased rental payments, consistent with these policies providing credit and allowing households to smooth consumption. To verify the robustness of these results, I confirm that similar eviction effects cannot be generated by assigning placebo winter protections to never-treated states. Additionally, I estimate a similar pattern of results when I leverage geographic variation in the share of renters excluded from winter protections—due to having oil heat or utilities included in rent—instead of energy burdens to identify the effect of winter utility shutoff protections.

This work contributes to the literature on the drivers of housing insecurity, the effects of credit access for low-income households, and the impacts of seasonal utility protections. Collinson et al. (2022) document that adverse health events, declining earnings and employment, and poor credit often precede an eviction filing. Causal evidence from changes to minimum wage policies suggests that minimum wage increases reduce renters defaulting on rental payments, hence lowering their risk of eviction (Agarwal et al. 2022). Health insurance coverage and access to treatment are also causal drivers of housing security. Evidence from ACA Medicaid expansions suggests that expanded coverage leads to reductions in eviction and eviction filing rates and that receiving Marketplace subsidies reduces rent and mortgage delinquencies (Gallagher et al. 2019; Zewde et al. 2019). Access to psychiatric treatment centers also lowers the eviction rate (Bradford and Maclean 2022). This paper contributes causal evidence on credit access as another key determinant of housing insecurity.

This paper also relates to the literature on consumption patterns and credit access among low-income households. It is well-established that low-income households face significant liquidity constraints (Agarwal et al. 2007; Johnson et al. 2006; Gross et al. 2014). Focusing on housing-insecure populations, Collinson et al. (2022) document that credit scores decline as households approach an eviction filing. To analyze the effects of credit access among low-income households, a large literature exploits changes to payday loan access. Evidence from payday loans, however, is mixed, with considerable evidence of both welfare gains (Zaki 2016; Dobridge 2018; Morgan et al. 2012; Bhutta et al. 2016; Wilson et al. 2010) and welfare losses (Melzer 2018; Zinman 2010; Skiba and Tobacman 2019; Campbell et al. 2012; Carrell and Zinman 2014; Gathergood et al. 2019). Most closely related to the focus of this paper on housing security, Melzer (2011) finds that payday loan access results in more difficulty paying mortgage, rent, and utility bills, while Morse (2011) provides contrasting evidence that payday loan access helps protect households affected by natural disasters from foreclosure. Conflicting evidence from payday loans on whether credit access can alleviate economic hardship may be due to the debt service burdens of predatory loans. In this paper, I study the effects of credit access in a unique setting by analyzing the ability to delay winter utility payments. This setting allows me to isolate the effects of credit access from the role of large debt service burdens included in payday loan estimates.

Lastly, this work contributes to the literature evaluating seasonal utility protections. Consumers appear to take advantage of winter shutoff protections by increasing natural gas consumption (Clark et al. 2017). During the COVID-19 pandemic, extensions of shutoff protections further benefited consumers by reducing COVID-19 infections and mortality rates (Jowers et al. 2021). On the supply side, public utilities do not appear overly burdened by these policies according to descriptive evidence from Iowa that while arrears are higher during shutoff protections, the number of unpaid bills remains relatively stable over the year (Colton 2003). This paper builds on evidence of these policies benefiting consumers by testing whether temporary access to credit is the mechanism by which shutoff protections improve consumer well-being.

The remainder of the paper continues as follows. Section 2 outlines the eviction filing process and policy details of winter utility shutoff protections. Section 3 discusses the data sources. Section 4 describes my empirical strategy. Section 5 reports the results. Section 6 provides a number of robustness checks. Section 7 concludes.

2 Background

2.1 Eviction Filings

Fifty-six percent of urban renters face some level of housing insecurity (Routhier 2019). Driven by difficulty paying rent, housing insecurity for renters can culminate in eviction proceedings.[2] A landlord initiates the eviction process by providing an eviction notice to a tenant. If the tenant does not pay past-due rent or voluntarily move out before the notice period expires, the landlord can file the eviction case in court.[3]

At this point, an eviction filing is public record regardless of the case outcome. An eviction-related public record, often called a "scarlet E", can appear on tenant screening reports for years and prevent renters from accessing quality housing (Goldstein 2021; Lake and Tupper 2021). Among eviction filings, just under half result in a court-ordered eviction (Desmond et al. 2018), which can cause homelessness and reduce earnings, durable consumption, and credit access for evicted tenants (Collinson et al. 2022). Many other filings are dismissed or discontinued after the tenant pays past-due rent or voluntarily moves out.

Some scholars characterize the landlord-tenant relationship surrounding eviction court as that of a creditor and debtor (Garboden and Rosen 2019). In line with this view, many landlords rely on the serial threat of eviction, repeatedly filing eviction cases against the same tenants (Leung et al. 2021; Garboden and Rosen 2019). For these landlords, filing an eviction is a means to collect rent more than it is a means to reclaim the property (Leung et al. 2021). Landlords report that collecting rent via serial eviction filings is more effective than attempts to pursue debts in civil court after a family has left the property (Garboden and Rosen 2019).

In this sense, a typical eviction filing can be conceptualized as a landlord's attempt to collect past-due rent or reclaim the property, which stains a tenant's record and carries a risk of displacement. Landlords have no incentive to grant additional credit to tenants before filing a case because for a relatively small fee, they can leverage the state for debt collection (Garboden and Rosen 2019).[4] This helps explains why a substantial share of tenants named in eviction filings owe less than one month of rent (Badger 2019). Access to small amounts of credit from external sources could in theory help tenants avoid a harmful eviction filing. However, Collinson et al. (2022) document that formal credit access deteriorates preceding an eviction filing, suggesting that these renters are severely credit constrained.

2.2 Winter Utility Shutoff Protections as Credit

Many states employ annual winter utility shutoff protections. These policies restrict public utility companies from disconnecting residential customers due to non-payment during a

[2] The vast majority of eviction filings are caused by non-payment of rent (Desmond 2012).

[3] The mandatory notice period before filing an eviction case in court varies by state but is typically between 3 and 10 days (Legal Services Corporation 2021).

[4] As of January 2021, the eviction filing fee in 22 states was below $100 (Abdelhadi and Ahmed 2021).

state-defined winter heating period.[5] In most cases, these policies date back to the 1970s or 1980s when the economic downturn and Arab oil embargoes led to difficulties affording winter heating costs (Standish and Sweet 1985; Schierman-Duncan 2011). While state motive behind these policies is to prevent exposure to cold temperatures, I argue that shutoff protections operate as a temporary extension of credit.

The credit access is equivalent to the ability to delay paying utility bills during the winter period. While winter energy bills accrued during protected periods are not forgiven, they can be at least partially foregone during this time without risk of disconnection nor utility debt appearing on a credit report. Utility companies do not report payment history nor accounts to credit bureaus, meaning that delayed payment of winter energy bills would not appear on a credit report.[6]

The amount of credit from shutoff protections is directly related to a household's winter heating costs. Between 2014 and 2019, the U.S. average winter heating costs ranged from $80-100 per month for households with natural gas heat and $174-196 per month for households with electric heat (EIA 2022). These costs and policy-induced credit can be higher in states with winter utility shutoff protections as they tend to face colder winter temperatures. The amount of credit is also related to whether a state's winter shutoff rule requires any minimum payment to avoid a winter disconnection.

The strongest winter shutoff protections prohibit utility disconnections during the winter period without requiring any minimum payment. For instance, Massachusetts mandates that "no company may shut off or refuse to restore utility service to the home of any customer if between November 15 and March 15 that the customer's service provides heat or operates the heating system and that the service has not been shut off for nonpayment before November 15th."[7] Similarly strong protections reserve the ban on disconnections for low-income households or those with children or elderly inhabitants.[8] Together, I refer to these strongest types of protections as "no disconnection" policies.

Other states require that residential customers make some minimum payment in order to

[5]Some states employ similar temperature-based protections which limit public utility disconnections if the temperature falls below a certain threshold—often 32°F. The temperature-based protections are more common in warmer states, meaning that they tend to bind for only short periods of time and offer virtually no access to credit. Therefore, I study solely date-based winter utility shutoff protections in this paper, and all references to winter utility shutoff protections are meant to specifically imply date-based versions of these protections.

[6]Utility non-payment can only affect credit if a utility provider sends debt to a collection agency.

[7]See 220 C.M.R. § 25.03(1).

[8]In many cases, the burden of proving whether a household is protected falls on public utility companies. This means that such eligibility thresholds may not bind if utilities opt not to expend resources investigating households' eligibility and instead refrain from disconnecting most residential customers. See Wis. Admin. Code §§ PSC 113.0304 for an example.

be protected from disconnection. For example, Minnesota mandates that "during the cold weather period, a utility may not disconnect and must reconnect utility heating service of a customer whose household income is at or below 50 percent of the state median income if the customer enters into and makes reasonably timely payments under a mutually acceptable payment agreement with the utility that is based on the financial resources and circumstances of the household; provided that, a utility may not require a customer to pay more than ten percent of the household income toward current and past utility bills for utility heating service."[9] I refer to these types of protections as "payment plan" policies.

Lastly, a number of states adopt "other" winter protections, such as granting households additional time to pay past-due bills after receiving a disconnection notice, additional notice before disconnecting, or a higher threshold of past-due bills necessary to initiate a disconnection. For the most part, I ignore any re-connection clause in states' winter shutoff rules since states inconsistently include such a clause and those that do, typically contain requirements that mirror that of the disconnection rule.[10] Table A1 lists the level of protection offered by each state that employs winter utility shutoff policies.

Given that the credit access made available by winter utility shutoff protections is temporary and relatively small in amount, I focus on families facing high credit constraints and energy burdens who have the potential to benefit from these policies. Credit-constrained renters near the margin of an eviction filing have a strong incentive to avoid an eviction filing by not falling behind or by catching up on rental payments. Therefore, I hypothesize that the credit access from winter shutoff protections allows renters to shift resources away from utility payments and toward rental payments, resulting in fewer eviction filings. Interviews with low-income renters in Milwaukee and Boston support exactly these consumption patterns (Desmond 2016; Halpern-Meekin et al. 2015). Before protections end in the spring, some renters report using EITC payments or other tax refunds to catch up on utility payments (Sykes et al. 2015).

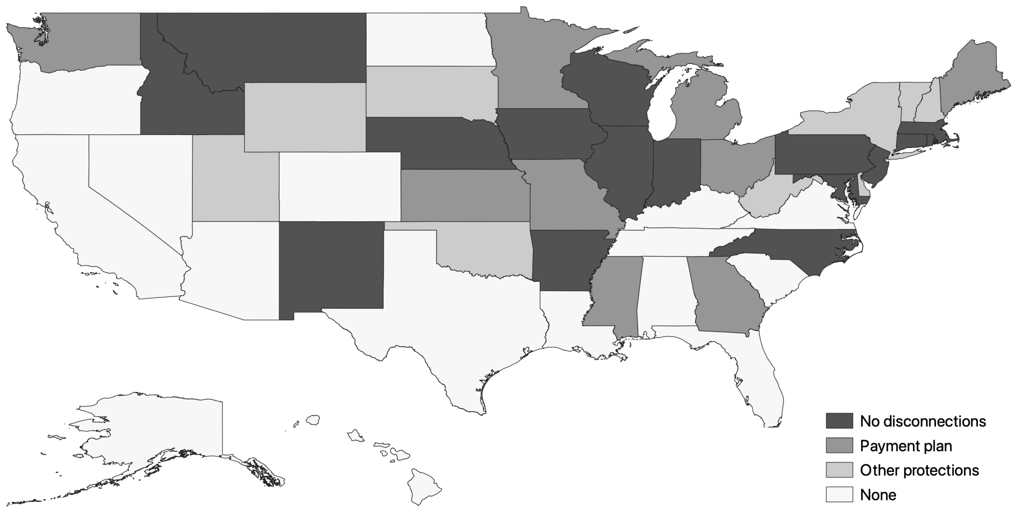
2.3 Policy Variation

Figure 1 depicts the 35 states that employed annual winter utility shutoff protections between 2010 and 2019. With some exceptions, states that utilize these protections tend to be located further north and face colder winter temperatures than states without winter shutoff protections. The protections turn on annually in the fall between October 1 to December 15 and turn off in the spring between March 1 to May 1. Between 2010 and 2019,

[9]See Minn. Stat. §§ 216B.096.

[10]Only in Ohio and Kentucky where the winter protection policy exclusively governs re-connections do I define the level of protection based on a re-connection clause.

Figure 1: Geography of Winter Protections (2010-2019)



nearly all states utilizing winter protections maintained their same annual start and end dates of the protected winter period. In a few select cases, states extended the protections later into the spring in response to harsh winters or other weather-related events.[11] See Table A1 for details on the timing of winter utility shutoff protections by state over the period of 2010 through 2019.

As intended by these policies, utility disconnections fall dramatically during periods of winter shutoff protections, as seen in Figure A1. Similarly cold states with no winter protections, do not exhibit the same sharp decreases in disconnections. The few cases of disconnections that do occur during protected periods can likely be attributed to households that failed to meet conditions for protection—e.g. defaulting on a payment plan, having outstanding debt from the previous winter, or falling outside the income range or demographic group for which protections are reserved.

[11]Massachusetts and Rhode Island extended protections in the spring of a number of recent years due to harsh winters. Iowa extended protections in the spring of 2019 due to extensive spring flooding that occurred across the state.

3 Data

3.1 Winter Utility Shutoff Protection Policies

I compile data on the annual start and end dates, level of protection, and other institutional details for state winter utility shutoff protections from current and archived state administrative codes. I focus on the period from 2010 through 2019, choosing not to analyze winter utility protections after the onset of the COVID-19 pandemic when the protections were extended, strengthened, and used in conjunction with eviction moratoria. See Table A1 for state policy details over the analysis period.

3.2 Eviction Filings

I source data on weekly eviction filings from the Eviction Lab's Eviction Tracking System (ETS). This data comes from 31 cities, 27 of which provide weekly eviction filings at the census tract level and the remaining 4 at the zip code level.[12] These cities were responsible for approximately 19% of all eviction filings in the U.S. between 2012 and 2019 (Gromis et al. 2022) and contain 16% of U.S. renter-occupied households. The ETS baseline data includes eviction filings by census tract for each week in an average year. The baseline years used to construct this variable vary by city, spanning some subset of years between 2012 and 2019. I exclude outlier census tracts with an average weekly eviction filing rate of greater than 5% from my analysis sample.[13]

Some census tract-week observations are partially covered by shutoff protections due to mid-week start and end dates or year-to-year changes in which week a calendar date falls. Around the start of winter protections, I define an active shutoff protection to correspond to a census tract-week being at least partially protected. Around the end of winter protections, I define an active winter shutoff protection to correspond only to a census-tract week that is entirely protected.[14]

[12] These cities include Albuquerque, Austin, Boston, Bridgeport, Charleston, Cincinnati, Cleveland, Columbus, Dallas, Fort Worth, Gainesville, Greenville, Hartford, Houston, Indianapolis, Jacksonville, Kansas City, Las Vegas, Memphis, Milwaukee, Minneapolis-St. Paul, New Orleans, New York, Philadelphia, Phoenix, Pittsburgh, Richmond, South Bend, St. Louis, Tampa, and Wilmington. Subsequently, I refer to units of observation in this dataset as census tracts despite including a small share of zip code level observations.

[13] Such high average weekly eviction filing rates are driven by places with very few renter-occupied households. In total, only 5 outlying census tracts are dropped from the sample under this criteria.

[14] In the fall when protections turn on, I do not want to mistakenly attribute any changes in eviction filings to the unprotected period preceding the start. In the spring when protections turn off, I do not want to mistakenly attribute any changes in eviction filings to the protected period preceding the end.

3.3 Rental Payments

To estimate how households shift rental payments during periods with winter utility shutoff protections, I utilize data from the interview portion of the Consumer Expenditure Survey (CES) from 2010 through 2019. This portion of the CES tracks households for a period of one year and asks quarterly about rental payments made in each of the three previous months, generating a twelve-month panel of rental payments for each household surveyed. The CES additionally asks households to report their utility bill amounts and annual income, which allows me to construct a measure of household energy burden.

3.4 Other Data Sources

I assemble data on annual census tract characteristics from the American Community Survey (ACS) and the Low-Income Energy Affordability Data (LEAD) Tool. The main annual variables sourced from the ACS include the number of renter-occupied households by heating source, median household income among renters, and the number of renter-occupied households for which utilities are included in rent. The LEAD Tool data compiles measures of census tracts' average annual energy burden in 2018 which captures the share of household income spent on energy costs. These measures are constructed from the 2016 5-year ACS after excluding households that have energy costs included in other housing costs.

Lastly, I utilize temperature data from the Global Historical Climatology Network on daily high, low, and average temperatures measured at over 66,000 land surface stations in the US. From this, I construct weekly high, low, and average temperatures for each city in the eviction data[15] and construct monthly high, low, and average temperatures for each state represented in the CES data.

3.5 Descriptive Statistics

From these data sources, I construct two main datasets on eviction filings and rental payments (Table 1). First, the eviction sample is a weekly panel of census tracts. On average, 160 per 100,000 renter-occupied households or about 0.16% of renters face eviction filings in a given week in my sample. I construct all temperature variables and census tract characteristics in the eviction sample as an average across the same set of baseline years as provided in the ETS data. Second, the CES renter sample is a monthly panel of renter-occupied households in the CES. These households appear to have relatively similar family

[15] Since the weekly eviction filing variables constitute an average across a set of baseline years, the weekly city temperature variables are constructed analogously using the relevant base years for each city.

Table 1: Descriptive Statistics

Panel A: Census Tract Data	Eviction sample			
	Mean	SD	Min	Max
Weekly eviction filings	1.58	5.61	0.00	262.00
Weekly eviction filings per 100k renters	159.85	266.91	0.00	20833.33
Avg. weekly city temperature (°F)	62.38	17.38	13.95	95.10
Renter-occupied households	902.31	1764.68	0.67	31793.17
Avg. energy burden among renters (%)	3.73	2.19	0.00	31.74
Median household income among renters	40953.16	22257.98	0.00	250001.00
Share of renters with gas heat (%)	41.00	28.81	0.00	100.00
Share of renters with electric heat (%)	53.39	30.80	0.00	100.00
Share of renters with oil heat (%)	2.73	9.04	0.00	100.00
Share of renters paying utilities (%)	90.87	12.61	0.00	100.00
Census Tract × Week Obs	447096			
Unique Census Tracts	8598			
Panel B: Household Data	CES renter sample			
	Mean	SD	Min	Max
Monthly rent payment (2010 USD)	820.26	579.02	0.00	6723.56
Avg. monthly state temperature (°F)	55.60	16.75	-8.03	88.19
Family income last 12 mths (2010 USD)	41931.78	42992.88	-110321.09	687251.00
Monthly energy* bill amount (2010 USD)	93.93	86.67	0.00	2603.60
Energy* burden (%)	5.49	10.60	0.00	100.00
Renter Household × Month Obs	237354			
Unique Renter Households	34227			

*Heating bills used to construct energy burdens include electricity and utility gas bills.

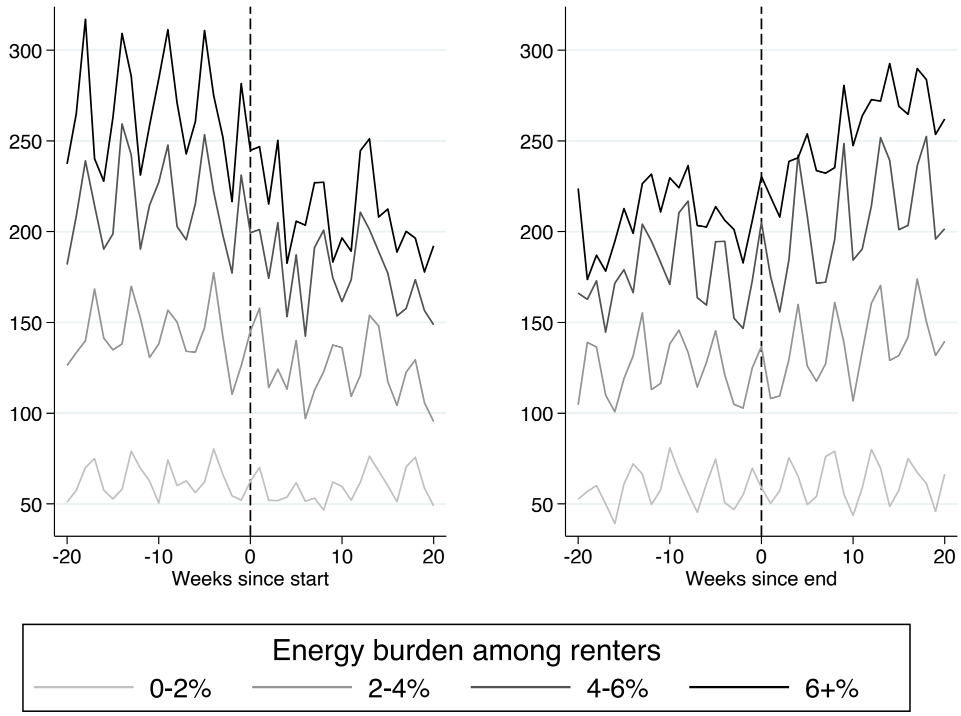
incomes to the median renter-occupied household in the eviction sample census tracts and also experience comparable average temperatures.

4 Empirical Strategy

4.1 Visual Evidence

To estimate the effect of credit access via winter utility shutoff protections on eviction filings, I first plot the eviction filing rate around the start and end of winter shutoff protections for groups of census tracts with different average energy burdens among renters (Figure 2). The eviction filing rate declines precisely during periods of winter utility shutoff protections, most starkly for high energy burden census tracts. When the winter protections end in the

Figure 2: Eviction Filings per 100,000 Renter-Occupied Households



This figure plots the average eviction filing rate around the start and end of winter utility shutoff protection periods. Energy burden among renters is defined at the census tract level as the ratio of average annual energy costs to average annual household income among renter-occupied households.

spring, eviction filings rise again in the same manner. I verify in Figure A2 that these raw trends are not driven by only one of the two components of energy burden—income or energy costs—alone, but by a combination of both.

4.2 Regression Estimates

While it is reassuring that the raw data does not exhibit any apparent trends leading up to the beginning or end of winter protections, my empirical approach aims to more definitively separate any effect of winter utility shutoff protections from any confounding trends in eviction filings by temperature or by energy burden level. The adoption and duration of winter shutoff protections is related to states' climates (Table A2).[16] Therefore,

[16]Conditional on the week, the average state weekly temperature predicts whether winter utility shutoff protections are active in that state and week. Depending on the polynomial form of temperature imposed, temperature can explain up to 2.5 percentage points more of the variation in whether a winter protection is active than week fixed effects alone.

temperature is a potential source of endogeneity if, for example, landlords altruistically avoid evicting tenants during cold weather periods. Another potential source of endogeneity stems from concerns that eviction filings in low energy burden areas may provide poor control trends for high energy burden areas.

I can address endogeneity concerns about temperature trends in eviction filings by exploiting within-state variation in the average energy burdens of census tracts. A within-state difference-in-differences (DD) approach identifies the effect of shutoff protections from comparisons between high and low energy burden census tracts in the same state and week before and after shutoff protections begin and end. This approach conditions on the temperature in the state and week but relies on low energy burden census tracts to provide control trends in eviction filings.

I can address concerns about low energy burden areas providing poor control trends in eviction filings for high energy burden areas by exploiting across-state variation in the timing of winter protections. An across-state DD approach is identified by comparing census tracts with similar energy burdens in the same week across states with and without active shutoff protections. This approach uses similarly energy burdened census tracts for control trends but is subject to temperature endogeneity concerns.

To address both potential sources of endogeneity, I adopt my preferred DDD approach which combines the within- and across-state DD strategies. The DDD approach allows me to separate the effect from state-wide weekly trends in eviction filings (which includes temperature trends) and from differential weekly trends in eviction filings for high and low energy burden areas. This DDD specification is as follows:

$$y_{ct} = \alpha_c + \delta_{st} + \sigma_{t \times HighEB} + \beta \; \mathit{ShutoffProtection}_{st} \times HighEB_c + X_{ct}^{'}\gamma + \epsilon_{ct} \tag{1}$$

The outcome of interest y_{ct} is eviction filings per 100,000 renter-occupied households in census tract c (in state s) in week t. $\mathit{ShutoffProtection}_{st}$ is an indicator for whether winter utility shutoff protections are active in state s in week t. $HighEB_c$ is an indicator for whether the census tract has a high average annual energy burden among renters, defined as greater than 5% of household income.[17]

I include census tract fixed effects, α_c, to control for time-invariant characteristics of census tracts. State-by-week fixed effects, δ_{st}, control for state-wide seasonal patterns in eviction filings. Notably, δ_{st} captures any relationship between the state's average weekly temperature and eviction filings. The $\sigma_{t \times HighEB}$ term constitutes energy burden group-by-week fixed effects. These fixed effects control for any differential seasonal patterns in

[17] This cutoff of 5% corresponds to approximately the 80th percentile of census tracts in the eviction sample according to their energy burdens among renters.

eviction filings for high and low energy burden areas. A within-state DD version of Equation 1 excludes the $\sigma_{t\times HighEB}$ term. An across-state DD version of Equation 1 excludes the δ_{st} term and includes an uninteracted variable $ShutoffProtection_{st}$.

While the δ_{st} term controls for any general relationship between temperature and the eviction filing rate, it is reasonable to think that any general relationship may be a function of income. For example, high income places with near-zero eviction filings year-round may not have any temperature-based changes in the filing rate. This may lead to biased estimates since energy burden is correlated with income. To address this, I include controls for polynomial forms of temperature interacted with income characteristics of census tracts in the X_{ct} term.

I cluster standard errors, ϵ_{ct}, at the census tract level and include observations from never-treated tracts in order to add precision to the parameter estimates. My coefficient of interest β captures the effect of being a high energy burden census tract during the winter shutoff protection period on the eviction filing rate. My identifying assumption is that in the absence of winter utility shutoff protections, the ratio of eviction filings for high energy burden census tracts relative to low energy burden census tracts in protected states would have continued to evolve in parallel to the same ratio of eviction filings in unprotected states, conditional on the temperature-varying controls X_{ct}. The assumption would be violated if the X_{ct} variables do not adequately control for any differential seasonal trends between protected and unprotected states in the ratio of eviction filings between high and low energy burden census tracts.

4.3 Event Study Estimates

I next estimate an event study specification to identify dynamic changes around the start and end of the protected winter period and evaluate the validity of the parallel trends assumption. Let w_s^{On} and w_s^{Off} be the starting and ending weeks, respectively, of the winter protected period in state s. Let W_s^{On} and W_s^{Off} be the number of weeks with and without winter protections annually in state s. I estimate the eviction effects i weeks after winter protections begin and end using the following specification:

$$
\begin{aligned}
y_{ct} =& \tilde{\alpha}_c + \tilde{\delta}_{st} + \tilde{\sigma}_{t\times HighEB} + \sum_{\substack{i=-13 \\ i\neq -1}}^{W_s^{On}} \beta_i^{Start} HighEB_c \times \mathbb{1}_{\{t-w_s^{On}=i\}} + \\
& \sum_{i=0}^{W_s^{Off}-13} \beta_i^{End} HighEB_c \times \mathbb{1}_{\{t-w_s^{Off}=i\}} + X_{ct}^{'}\lambda + e_{ct}
\end{aligned}
\tag{2}
$$

The β_i^{Start} coefficients estimate the effect of imposing winter utility shutoff protections i weeks after they begin for high energy burden census tracts. I estimate β_i^{Start} coefficients for the 13 weeks preceding the start of protections and for the duration of the winter protected period, omitting the week prior to the start of protections. The coefficients for $i < 0$ allow me to evaluate whether protected states' trends in the ratio of eviction filings between high and low energy burden census tracts are parallel to the ratio in unprotected states prior to the start of winter protections. I can also explore how eviction filings evolve after winter utility shutoff protections end in the spring by including the β_i^{End} parameters to estimate the effect i weeks after the protections end. I estimate these β_i^{End} coefficients for the range of weeks spanning the end of protections through 13 weeks prior to the next start, which corresponds to the set of weeks not already modeled by the β_i^{Start} parameters. In other words, I estimate β coefficients corresponding to every week of the year for places with winter utility shutoff protections, omitting only the week prior to the start of protections. Comparing the magnitudes of the β_i^{Start} and β_i^{End} estimates can shed light on the total effect of winter utility shutoff protections and whether any reductions in eviction filings during protected periods represent filings delayed until immediately after the protections end.

5 Results

5.1 Eviction Filing Results

I find that temporary credit extended via winter utility shutoff protections improves housing security. Census tracts facing high average energy burdens experience a significant reduction in weekly eviction filings while winter utility shutoff protections are active. After controlling for temperature-varying trends by income level in my preferred DDD specification, I estimate that weekly eviction filings decline by 9.7 per 100,000 renter-occupied households in high energy burden census tracts (column 6 of Table 2). Relative to periods of the year without shutoff protections in high energy burden tracts, this effect is equivalent to a 4% decline in the eviction filing rate. To the extent that winter shutoff protections also cause a decrease in eviction filings in census tracts with average energy burdens below 5%, these estimates may underestimate the true causal effect. Alternative specifications that rely solely on the within-state variation (columns 1-2 of Table 2) do not use high energy burden tracts in states without active protections for control trends. Across-state estimates reported in columns 3-4 of Table 2 do not use same-state low energy burden tracts for control trends. The within-state estimates are larger in magnitude than the across-state estimates and my preferred DDD estimates, which verifies the importance of controlling for eviction trends in

Table 2: Eviction Filings per 100,000 Renter-Occupied Households

	Eviction Filings per 100,000 Renter-Occupied Households					
	Within-State		Across-State		DDD	
	(1)	(2)	(3)	(4)	(5)	(6)
Shutoff Protection × High EB	-22.44***	-18.21***	-11.04***	-12.20***	-7.068**	-9.690***
	(2.111)	(2.389)	(3.124)	(3.164)	(2.880)	(2.972)
Observations	446368	446368	446368	446368	446368	446368
Adjusted R^2	0.416	0.416	0.386	0.386	0.416	0.416
Outcome Mean	159.85	159.85	159.85	159.85	159.85	159.85
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	Yes	No	No	Yes	Yes
Week × HighEB FE	No	No	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates of β from Equation 1. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

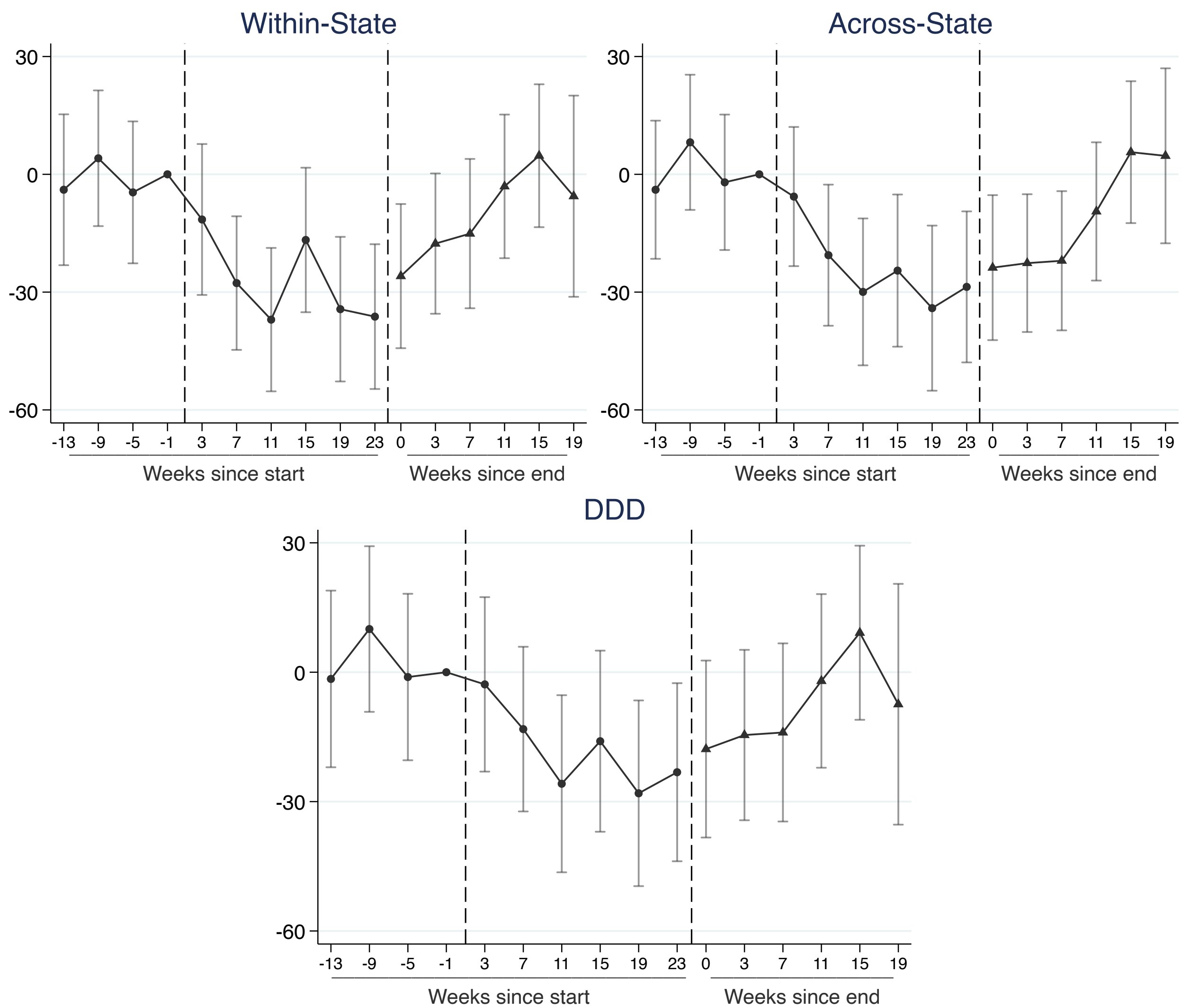
high energy burden tracts in states without active shutoff protections.

Next, I plot in Figure 3 the event study estimates of dynamic changes in eviction filings per 100,000 renter-occupied households. Each of the plotted coefficients is the average of the β_i estimates from Equation 2 within 4-week bins. The circular points on the left correspond to the β_i^{Start} estimates while the triangular points on the right correspond to the β_i^{End} estimates. The interpretation of both sets of estimates is the average change in weekly eviction filings per 100,000 renter-occupied households in high energy burden census tracts relative to the week prior to the start of protections.

These plots demonstrate that the decline in eviction filings during the winter period documented in Table 2 is generated by eviction filings decreasing after protections turn on in the fall and increasing again back to pre-protection levels after they turn off in the spring. These plots are also consistent with the parallel trends assumption, as the coefficients before the start of winter protections are not statistically different from zero nor exhibiting any significant trend. This suggests that the control variables consisting of temperature-varying trends by income characteristics of census tracts are sufficiently accounting for any endogenous seasonal patterns in the high-low energy burden ratio of eviction filings that differs between protected and unprotected areas.

The general pattern of estimates and the magnitude of the protection-induced decline in eviction filings is strikingly similar across specification in Figure 2. By the time the

Figure 3: Eviction Filings Event Study



This figure plots point estimates β_i^{Start} and β_i^{End}, described in Equation 2, of the effect of winter protections on eviction filings per 100,000 renter-occupied households. The plotted coefficients are the average of the weekly β_i estimates across 4-week intervals. All point estimates are estimated relative to the single week prior to the start of winter protections. The regressions generating these point estimates control for quintiles of median household income among renters interacted with a quadratic in average weekly temperature and cluster standard errors at the census tract level.

changes induced by the winter protections stabilize, high energy burden census tracts are consistently estimated to have approximately 30 fewer eviction filings per 100,000 renters. This is more than triple the magnitude of the average effect (9.7) reported in column 6 of Table 2. The difference in magnitudes across the specifications in Table 2 appears to be driven by differences in how quickly eviction filings begin to decline following the start of the protections. The DDD and across-state specifications rely more heavily on the limited variation and fuzzy assignment of winter utility shutoff protection dates in the eviction sample, which can help explain the less immediate decline in filings under these specifications in Figure 3 and the smaller magnitudes in Table 2.[18]

An important consideration when interpreting these results is whether the documented decline in eviction filings represents filings that are delayed until immediately after the winter period ends or filings that are prevented for some longer period of time. At a minimum, the entirety of "missing" eviction filings during the winter period are shifted until the protections end in the spring. Even if this is the case, temporarily-delayed eviction filings can generate substantial welfare gains if fewer people face potential housing loss during periods of dangerously cold temperatures. Alternatively, the temporary credit may allow vulnerable households to avoid an eviction filing for a longer period of time beyond the end of the winter protections.

Given that the β_i^{Start} and β_i^{End} coefficients are comparable in magnitude, Figure 3 can distinguish between these interpretations. If it were true that eviction filings are delayed until immediately after the winter protections end, I would expect to find a large increase in filings after the end date that then diminishes over time. Contrary to this case, I do not find any evidence that the β_i^{End} estimates are at all elevated after the end date as compared to the pre-start levels. Instead, the β_i^{End} estimates suggest that eviction filings gradually rise, returning to pre-protection levels roughly 11 weeks after the protections end. This evidence of persistent yet diminishing effects of the temporary line of credit past the policy end date suggests that the winter protections do not simply shift eviction filings until the end date.

5.1.1 Heterogeneity by Credit Amount

Next, I test whether larger amounts of credit from winter utility shutoff protections generate greater declines in eviction filings. Given that the amount of credit is related to the dollar amount of energy bills, I predict that the protections provide more credit and thus greater declines in eviction filings when winter temperatures are the lowest and heating costs are the highest. Since the credit accumulates during the winter shutoff protection period, the relevant temperature variable is the running average temperature since the shutoff protections began. I present estimates of heterogeneous effects of winter utility shutoff protections by the running average weekly temperature in Table 3. These results are consistent with the winter utility shutoff protections generating the largest declines in eviction filings when and where preceding temperatures have been the coldest.

[18] The eviction sample includes just 4 unique starting weeks and 5 unique ending weeks, all of which occur within narrow start and end windows. Further, the data structure of the eviction sample requires fuzzy assignment of winter protected periods in cases where, for instance, the protections ended in week 13 in 2012 but week 14 in 2013.

Table 3: Heterogeneous Effects by Temperature

	Eviction Filings per 100,000 Renter-Occupied Households		
	Within-State (1)	Across-State (2)	DDD (3)
Shutoff Protect. × High EB × ≤ 35° F	-24.99***	-42.97***	-20.76***
	(5.095)	(5.113)	(6.034)
Shutoff Protect. × High EB × 35-40° F	-19.49***	-9.699***	-12.32***
	(2.745)	(3.617)	(3.510)
Shutoff Protect. × High EB × 40-45° F	-21.27***	-12.12***	-8.492**
	(3.141)	(3.799)	(3.726)
Shutoff Protect. × High EB × 45-50° F	-13.40***	-12.82***	-5.833
	(3.936)	(4.723)	(4.781)
Shutoff Protect. × High EB × > 50° F	6.077	23.85***	10.48*
	(5.026)	(5.192)	(5.605)
Observations	446368	446368	446368
Adjusted R^2	0.416	0.386	0.416
Outcome Mean	159.85	159.85	159.85
Census Tract FE	Yes	Yes	Yes
Week × State FE	Yes	No	Yes
Week × High EB FE	No	Yes	Yes
Controls	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates of heterogeneous effects of winter protections on eviction filings. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. The temperature bins correspond to the running average weekly temperature within the winter shutoff protection period. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

States with the strongest protections—those considered "no disconnection" policies—provide larger amounts of credit than those that mandate enrolling in a payment plan to be protected from winter disconnections. Surprisingly, estimates in columns 1-3 of Table 4 suggest that the decline in eviction filings attributed to winter utility shutoff protections is seemingly unrelated to the level of protection offered. This is due to states with the strongest policies also having a larger share of renters excluded from accessing the credit. Households with oil heat do not have access to these protections since the protections solely govern electricity and utility gas companies.[19] Similarly, renters that have utilities included in their rental payments cannot delay these payments and thus lack access to the credit provisions of winter utility shutoff protections.

[19] Anecdotally, Massachusetts has a relatively high share of renters using oil heat and also mandates a "no disconnection" policy.

Table 4: Heterogeneous Effects by Level of Protection

	Eviction Filings per 100,000 Renter-Occupied Households					
	Full Sample			Restricted Sample		
	(1) Within	(2) Across	(3) DDD	(4) Within	(5) Across	(6) DDD
No disconnect × High EB	-17.53***	-11.68***	-9.124***	-28.14***	-34.00***	-22.66**
	(2.971)	(3.713)	(3.486)	(8.999)	(8.799)	(9.293)
Payment plan × High EB	-19.05***	-11.26***	-10.41***	-19.26***	-12.42**	-12.44**
	(3.376)	(3.766)	(3.777)	(4.904)	(5.642)	(5.419)
Other × High EB	-18.84	-9.414	-10.04	-25.33	-13.13	-18.60
	(13.13)	(13.25)	(13.34)	(18.76)	(18.73)	(18.89)
Observations	446368	446368	446368	248820	248872	248820
Adjusted R^2	0.416	0.386	0.416	0.388	0.362	0.388
Outcome Mean	159.85	159.85	159.85	173.63	173.63	173.63
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	No	Yes	Yes	No	Yes
Week × High EB FE	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No disconnect = Payment plan						
p-value	0.711	0.917	0.757	0.363	0.0193	0.298

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates of heterogeneous effects of winter protections on eviction filings. The restricted sample excludes census tracts with any renters using oil heat and census tracts with over 10% of renters with utility costs included in rent. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

Estimates reported in columns 4-6 of Table 4 illustrate that heterogeneous effects of winter utility shutoff protections emerge when focusing on a sample of census tracts with few excluded renters. Here, "no disconnection" policies generate larger declines in eviction filings than "payment plan" policies, although I am unable to precisely reject that the coefficients are the same in my preferred DDD specification. The heterogeneous effects of "other" policies cannot be interpreted with much confidence. Just two states in the eviction data—New York and Delaware—fall into the "other" category, and New York's winter protections could arguably be classified as a "no disconnection" policy.[20]

Since non-white households tend to face higher credit constraints than white households

[20]New York's annual winter utility shutoff policy guarantees additional notice prior to disconnection for all, but mandates no disconnections if doing so is determined to be a health risk. Within New York's protected period (November 1 - April 15), disconnections are also entirely prohibited during the 2-week period which includes Christmas and New Years.

(Cohen-Cole 2011; Weller 2009), credit access from winter utility shutoff protections should generate larger reductions in eviction filings in census tracts with more non-white renters. In Table A3, I find that the declines in eviction filings in high energy burden census tracts are indeed driven by tracts with a majority of renters being non-white. This result is consistent with the temporary credit access providing the greatest benefit to the most credit-constrained families.

5.2 Rental Payment Results

Next, I test whether credit access explains this decline in eviction filings caused by winter utility shutoff protections. For credit access to reduce eviction filings, rental payments must rise during protected winter periods for renters facing high energy burdens. My preferred DDD estimate in column 6 of Table 5 suggests that winter utility shutoff protections generate a 3.2% increase in monthly rental payments among renters facing high energy burdens. This result is consistent with credit from winter shutoff protections allowing vulnerable renters to smooth consumption and divert resources toward rental payments.

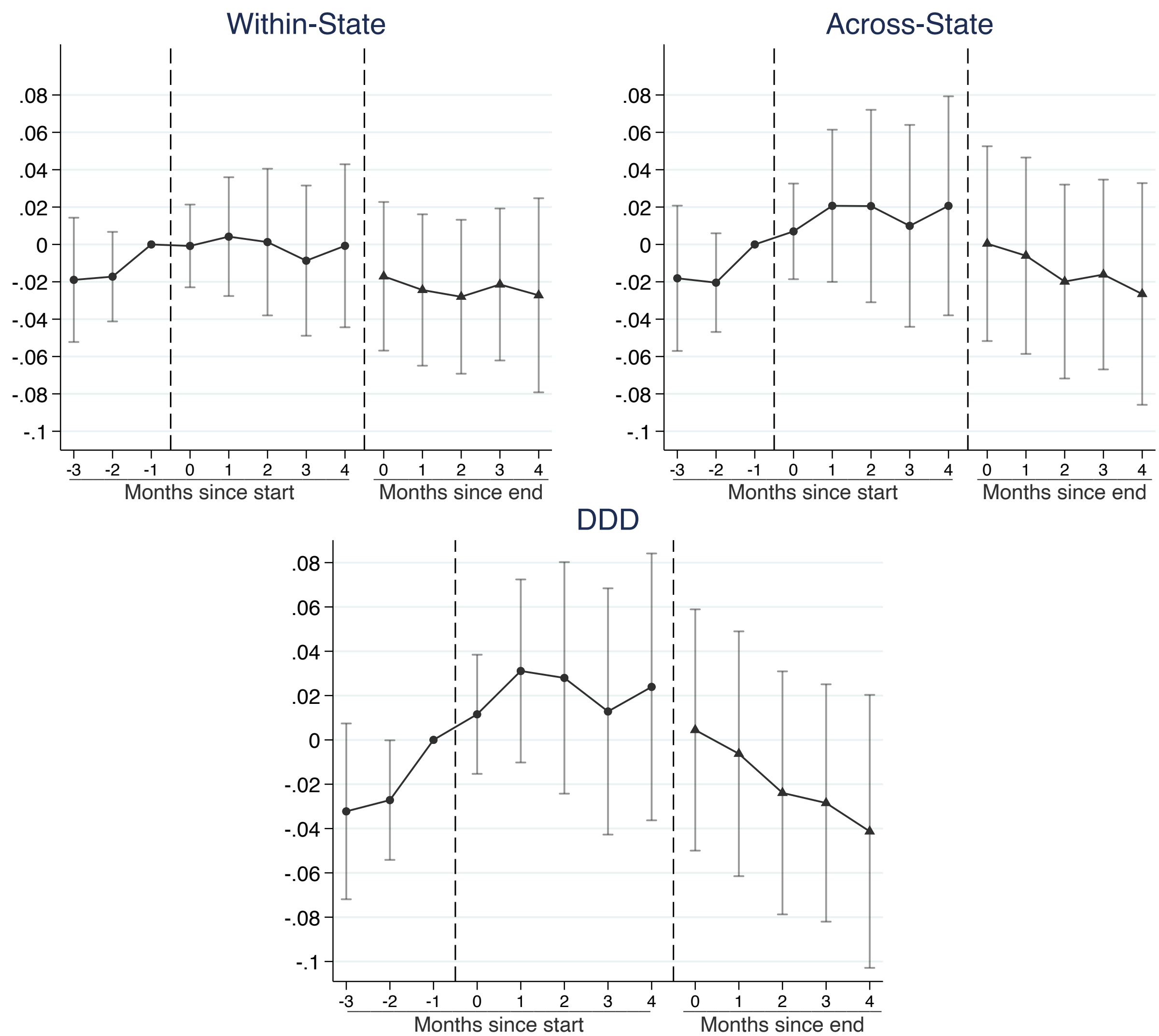
Table 5: Rental Payment Results

	Ln(Monthly Rent Payments + 1)					
	Within-State		Across-State		DDD	
	(1)	(2)	(3)	(4)	(5)	(6)
Shutoff Protection × High EB	0.0170	0.0152	0.0205	0.0230	0.0287*	0.0316**
	(0.0126)	(0.0131)	(0.0152)	(0.0154)	(0.0157)	(0.0159)
Observations	236626	236626	236660	236660	236626	236626
Adjusted R^2	0.852	0.852	0.850	0.850	0.852	0.852
Outcome Mean	6.36	6.36	6.36	6.36	6.36	6.36
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Month × State FE	Yes	Yes	No	No	Yes	Yes
Month × High EB FE	No	No	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates of the effect of winter shutoff protections on high energy burden households using a sample of renter-occupied households in the CES. Households are classified as having high energy burdens if their average gas and electric bill amounts are more than 5% of their reported income. Controls include quintiles of household income interacted with a quadratic in average monthly temperature. Standard errors are clustered at the household level.

I also estimate dynamic changes in monthly rental payments around the start and end of winter utility shutoff protections in Figure 4. Rental payments appear to rise when protections turn on in the fall and decline in the spring after protections turn off. The

Figure 4: Log Monthly Rental Payments



This figure plots monthly point estimates of the dynamic effect of winter protections on the natural log of monthly rental payments around the start and end of winter protections. The sample is restricted to renter-occupied households in the CES. Households are classified as having high energy burdens if their average gas and electric bill amounts are more than 5% of their reported income. The regressions generating these point estimates control for quintiles of household income interacted with a quadratic in average monthly temperature. Standard errors are clustered at the household level. Coefficients corresponding to five months after the start of protections and five months after the end of protections are estimated but omitted from this figure because few state protections span this duration which generates severely imprecise estimates. See Figure A3 for plots including these coefficients.

protection-induced rise in rental payments, however, appears to slightly precede the policy start date. The start and end dates of winter utility shutoff protections are widely known, but only once renters can delay their utility payments without risking a disconnection can they access the credit. Thus, any rental payment responses in anticipation of the protections could only occur after the final utility payment due date prior to the start of the protections. The estimates plotted in Figure 4 are consistent with this type of limited anticipation of the policy. It does not violate policy exogeneity assumptions but instead provides suggestive evidence that access to credit from shutoff protections indeed begins after the final utility payment due date prior to the policy start date. Furthermore, the time between a missed rental payment and an eviction filing is likely at least a month (Badger 2019). As such, it is reassuring that the policy-induced increase in rental payments documented in Figure 4 precedes the policy-induced decline in eviction filings documented in Figure 3.

5.2.1 Comparing Rental Payment Effects to Credit Amount

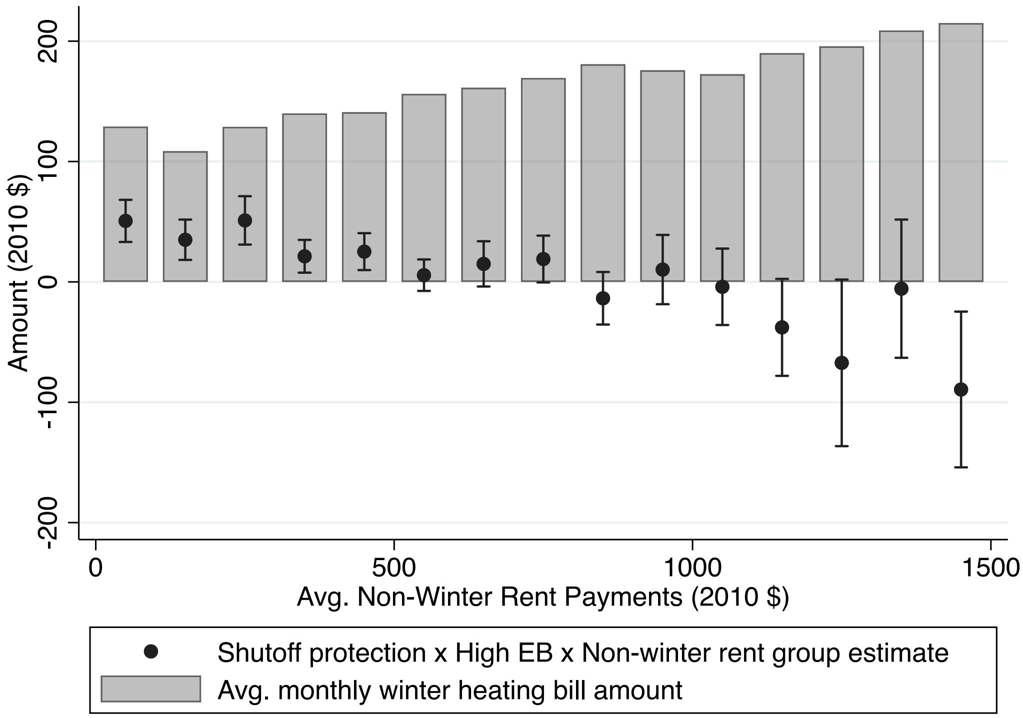
The magnitude of this increase in rental payments for energy-burdened renters together with information on heating bill amounts can offer insight into exactly how much credit from delayed utility bills is being allocated toward rental payments. I estimate a heterogeneous version of the rental payments DDD specification to capture the protection-induced increase in rental payments for groups of energy-burdened renters who made similar non-winter rental payment amounts. I revert the outcome variable to be a continuous value of monthly rental payments measured in 2010 dollars. In Figure 5, I plot these heterogeneous DDD estimates. I also plot the average monthly winter heating bill amounts within these groups to provide a sense of the maximum credit from the winter protections available to them. Figure 5 illustrates that the protection-induced increase in rental payments is driven by renters that made average rental payments of less than \$800 during months with no winter shutoff protections. The magnitude of the increase in rental payments reaches \$49.32 among the typically lowest-paying renters, which is equivalent to 37.36% of the maximum heating bill credit available to them.

6 Robustness Checks

6.1 Robust Specifications

My main regression results rely on the assumption that the temperature-by-income variables adequately control for any differential seasonal trends between protected and unprotected states in the ratio of eviction filings for high energy burden census tracts relative to low energy burden census tracts. If these controls are sufficient, then my main results should be robust to including more flexible versions of these control variables. Table A4 restates my main DDD result in column 1 of panel A and confirms that this result is insensitive to introducing temperature-by-poverty controls, interacting the temperature-by-income and

Figure 5: Rental Payment Increases Relative to Utility Bill Credit



This figure plots the heterogeneous effects of winter utility shutoff protections on the continuous measure of monthly rental payments. Each plotted point estimate represents the effect of winter utility shutoff protections for renter-occupied households facing high energy burdens within each respective group of households. The renter-occupied households are divided into groups based on their average monthly rental payments during months not protected by winter utility shutoff policies. Overlayed are the average monthly heating (electric and utility gas) bill amounts for renter-occupied households facing high energy burdens within each respective group.

temperature-by-poverty controls with region dummies, and altering the form of temperature from a quadratic to a cubic or 5°F bins.

I also verify that my results are not dependent on the specific definition of high average energy burden (> 5%). Table A5 reports results using the four levels of energy burden that correspond to Figure 2. Consistent with my main results, I find that the protections increasingly prevent eviction filings in census tracts with 2-4%, 4-6%, and 6+% energy burden relative to places with 0-2% average energy burden. The DDD specifications are somewhat under-powered when estimating effects for a greater number of energy burden groups but generate patterns of estimates that are broadly consistent with my main results.

My identification strategy relies in part on control trends in eviction filings from low energy burden census tracts. A more robust set of control trends excludes the lowest energy burden tracts with less than 2% average energy burden among renters. Panel A of Table A6 confirms that my main results are robust to excluding these census tracts. Similarly, census tracts that never have any eviction filings may not be suitable controls. My results are also robust to excluding census tracts with 0 eviction filings over the entire sample period (panel B of Table A6).

Next, I confirm that my results are unaffected by clustering at alternative levels. Since treatment—a high energy burden census tract under winter utility shutoff protections—varies at the census tract level, I cluster standard errors at the census tract level. However, given that the timing of winter utility shutoff protections is determined by states, I report more conservative standard errors clustered at the state level in Table A7. The state clustering may generate other concerns about having too few—19—clusters in the eviction data. Therefore, I also report 90% confidence intervals derived from a wild-cluster bootstrap procedure.

6.2 Placebo Tests

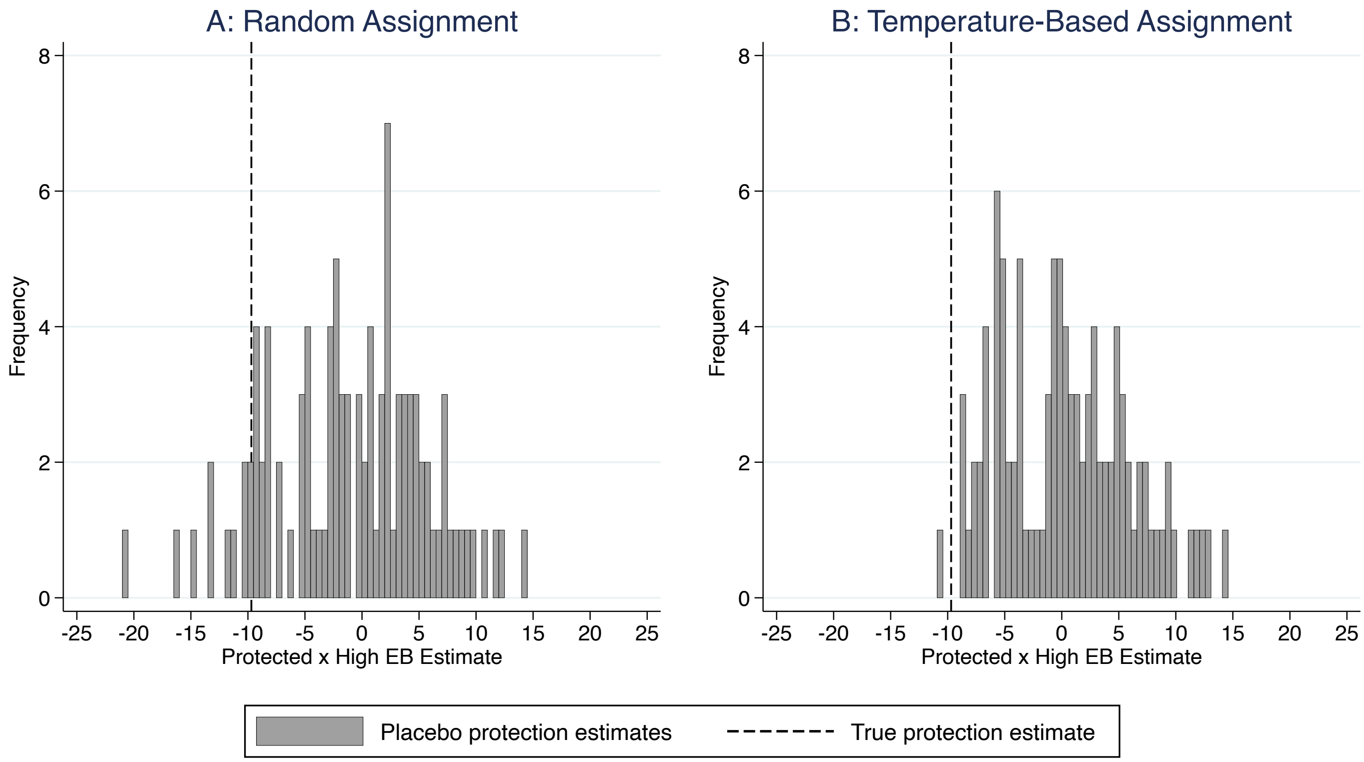
To further strengthen the validity of these results, I rule out the possibility that similar results could be generated by assigning placebo winter protection periods to never-treated states. I first randomize placebo winter protection periods to states without protections, selecting from the set of actual start and end dates.[21] I then estimate my DDD specification including controls to estimate any effect of placebo winter protections using the sample of never-treated states. I replicate this randomization 100 times and plot the placebo point estimates in panel A of Figure 6. My estimate of the effect of true winter protections is an outlier compared to estimates generated by randomly-assigned placebo winter protections.

Since never-treated states tend to be much warmer than states with winter protection periods, a more realistic placebo protected period may account for the temperatures in never-treated states. For each never-treated state, I draw placebo start and end temperatures from a normal distribution of true start and end temperatures observed in treated states. Next, I select the weeks in each never-treated state that correspond most closely to that state's drawn placebo start and end temperatures. When doing this, I restrict the possible range of placebo winter protection periods to start between October 1 and January 31 and end between February 1 and May 31. I repeat these draws 100 times and estimate my DDD specification with controls to estimate any effect of placebo winter protections on the sample of never-treated states.

Panel B of Figure 6 reports the distribution of temperature-based placebo estimates. Again, my estimate of the effect of true winter protections is an outlier compared to the

[21] Possible start dates include October 15, November 1, November 15, and December 1. Possible end dates include March 1, March 15, April 1, April 15, and May 1.

Figure 6: Eviction Effects from Placebo Winter Protections



This figure plots DDD estimates of the effect of placebo winter protections on eviction filings per 100.000 renter-occupied households using a sample of never-treated states. The vertical dashed lines correspond to the actual estimated effect of true winter protections reported in column 6 of Table 2.

temperature-based placebo estimates. It is also reassuring that the DDD specification generates unbiased placebo estimates under both random and temperature-based assignment of placebo protections. This is consistent with no confounding seasonal trends in eviction filings biasing my main DDD results.

6.3 Alternative Treatment Definition

Since these placebo tests are run on a sample of never-treated states that are distinctly warmer than ever-treated states, concerns may remain about differential seasonal trends due to the fact that the range of temperatures in never-treated states may not be able to adequately mimic any temperature-varying trends in treated states. To address this, I exploit two types of housing characteristics that exclude renters from gaining access to winter utility shutoff protections and are arguably more randomly-assigned and less likely to exhibit differential seasonal trends than energy burden: oil heat usage and inclusion of utilities in rent.

First, these protections do not apply to households with oil heat because the policies exclusively govern regulated public utilities—electric and gas. Second, winter utility shutoff protections cannot act as a line of credit for renters that have utilities included in their rent. These renters lack the ability to delay winter energy payments even if winter utility shutoff protections are in place. If my main estimates that exploit energy burdens are indeed spurious due to differential seasonal trends, I should not find similar declines in eviction filings when exploiting variation in these alternative housing characteristics. As an aside, I do not leverage these housing characteristics in my main analysis because the prevalence of oil heat and inclusion of utilities in rent is quite low and almost never applies to the majority of renters in a census tract. Nevertheless, I exploit what limited variation exists in these characteristics to confirm that this approach generates a similar pattern of results to my main estimates.

To implement this approach, I utilize a similar specification to Equation 1 but exploit geographic variation in oil heat usage and inclusion of utilities in rent in place of energy burdens. I replace the $HighEB_c$ variables in Equations 1 with an indicator for whether census tract c contains less than 15% of renters excluded from winter utility shutoff protections. I construct three separate definitions of excluded renters. The first applies the 15% cutoff to the share of renters using oil heat, the second applies the cutoff to the share of renters with utilities included in their rent, and the third applies the cutoff to either of the two housing characteristics.[22] I report estimates of the treatment effects of winter utility shutoff protections using this approach in Table A8.

I broadly find that the protections cause a decline in eviction filings for areas with few excluded renters relative to areas with many excluded renters. This finding is consistent across the three definitions of excluded renters. This specification differences out changes in areas with many excluded renters, but up to 85% of renter-occupied households in control areas may stand to gain from the protections. To the extent that winter shutoff protections also cause a decrease in eviction filings in these control census tracts, these estimates underestimate the true causal effect.

Among census tracts with few renters excluded from winter protections based on these housing characteristics, I still predict heterogeneous effects based on the average energy burden since energy burden dictates the amount of credit provided by the protections. Notably,

[22]I choose a threshold of 15% based on the distribution of the housing characteristics that exclude renters from the protections granted by winter utility shutoff policies. In the median census tract, just 4% of renters have utilities included in their rent and 0% of have oil heat. The 15% threshold falls at the 94th percentile of census tracts according to the share of renters with oil heat and at the 80th percentile of census tracts according to the share of renters with utilities included in rent.

my measure of a census tract's average energy burden among renters is unrelated to the prevalence of utilities being included in rent.[23] Adopting the same strategy that leverages variation in renters being excluded from the winter protections, I estimate heterogeneous effects for high and low energy burden areas and report the results in Table A9. I find that the effect of winter utility shutoff protections based on variation in the share of excluded renters is indeed heterogeneous, generating significantly larger declines in eviction filings in places with high average energy burdens. For the most part, I can precisely reject that the effects from this approach are equivalent in high and low energy burden census tracts.

Overall, it is reassuring that estimates based on variation in oil heat and inclusion of utilities in rent confirm that winter protections cause a decrease in eviction filings with statistically larger declines in places with higher average energy burdens. Given that rates of excluded renters under each of the definitions tend to be quite low, the treatment threshold of 15% implies that up to 85% of renter-occupied households in control areas may also respond to the protections. In this sense, the magnitudes estimated here are not necessarily comparable to my main estimates.

7 Conclusion

I find that temporary credit extended via winter utility shutoff protections causes a significant decline in eviction filings. Census tracts with renters facing high energy burdens experience approximately 9.7 fewer weekly eviction filings per 100,000 renter-occupied households when the protections are active. Estimates of dynamic changes in eviction filings around the start and end of protected periods suggest that after the protection-induced changes stabilize, this decline reaches approximately 30 fewer filings per 100,000 renter-occupied households. Aggregating the dynamic estimates over all U.S. census tracts facing high average energy burdens, winter utility shutoff protections prevent over 23,000 eviction filings during an average winter.[24] This number is likely an underestimate. I further demonstrate that the decline in eviction filings attributed to winter utility shutoff protections is driven by increased rental payments, consistent with these policies providing credit.

While many types of interventions attempt to reduce homelessness and eviction, only some generate meaningful results and can come at significant costs (Evans et al. 2021). This

[23] Households who have energy costs included in other housing costs such as rent are excluded from the calculation of a census tract's average energy burden among renters. This means that I observe some census tracts with both high energy burdens and also relatively high rates of utilities being included in rent which allows me to estimate these heterogeneous effects.

[24] This estimate is based on the entire set of regression coefficients plotted in the DDD panel of Figure 3 which allows for spillovers after the end of winter protections.

paper provides evidence of a seasonal policy that unintentionally helps address the important public policy goal of improving housing security. I provide evidence that winter utility shutoff protections generate significant reductions in eviction filings, preventing renters from arriving at the critical juncture of facing housing loss. This is also beneficial to landlords who receive the 3.2% increase in rental payments and avoid costs associated with an eviction filing.[25] Additionally, the effectiveness of winter shutoff protections seems to come at a minimal cost. Public utilities do not appear to be overly burdened by complying with these protections (Colton 2003), which is supported by renters' reports of using EITC payments to catch up on utility debt in the spring (Sykes et al. 2015). However, more rigorous evidence is needed to fully understand the supply-side implications of winter shutoff protections.

The fact that access to credit is the key mechanism by which winter utility shutoff protections prevent eviction filings suggests that credit considerations should be central to the development of future housing assistance policies for renters. Such a small and temporary extension of credit generating significant improvements in housing security implies a high value for policies to promote credit access among constrained renters.

[25] TransUnion estimates that an average eviction proceeding can cost landlords $3500 (TransUnion 2016).

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A Appendix

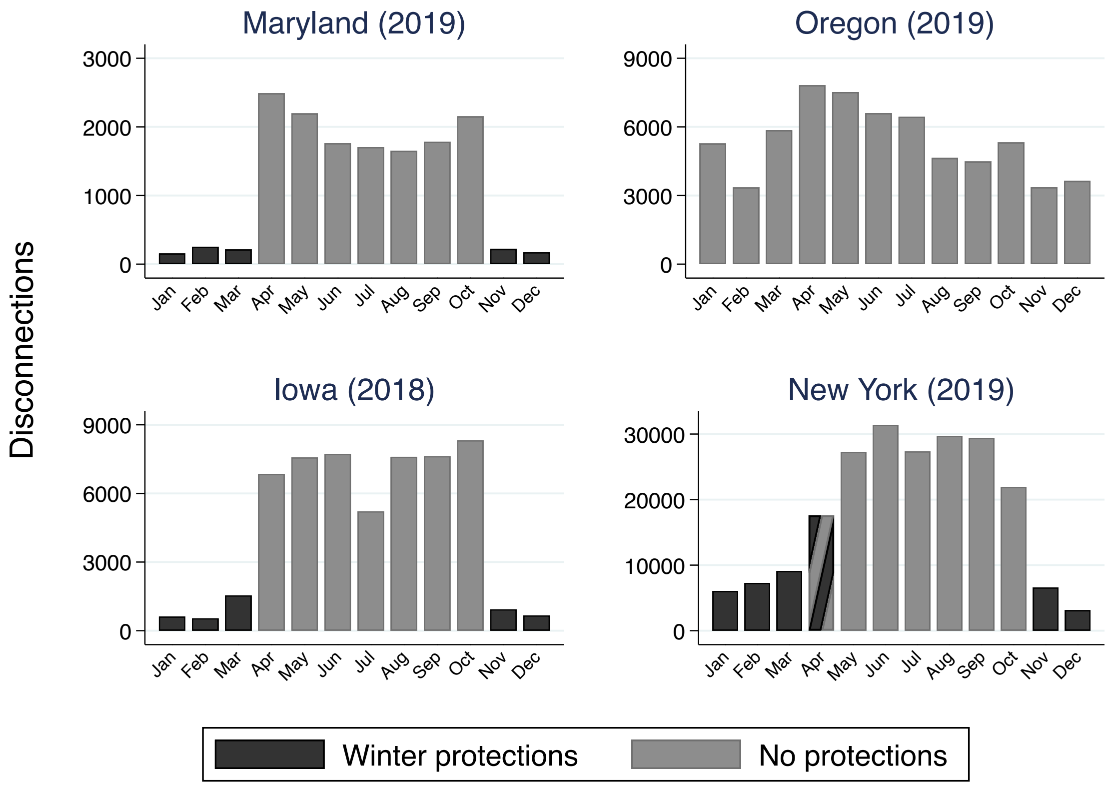
Table A1: Winter Utility Shutoff Protections (2010-2019)

State	Type	Start Date	End Date
Arkansas	No disconnection	Nov. 1	Mar. 31
Connecticut	No disconnection	Nov. 1	May 1
Delaware	Additional notice	Nov. 15	Mar. 31
Georgia	Payment plan	Nov. 15	Mar. 15
Idaho	No disconnection	Dec. 1	Feb. 28
Illinois	No disconnection	Dec. 1	Mar. 31
Indiana	No disconnection	Dec. 1	Mar. 15
Iowa	No disconnection	Nov. 1	Apr. 1 (extended in 2019)
Kansas	Payment plan	Nov. 1	Mar. 31
Kentucky	Payment plan	Nov. 1	Mar. 31
Maine	Payment plan	Nov. 15	Apr. 15
Maryland	No disconnection	Nov. 1	Mar. 31
Massachusetts	No disconnection	Nov. 15	Mar. 15 (extended in 2010-12)
Michigan	Payment plan	Nov. 1	Mar. 31
Minnesota	Payment plan	Oct. 15	Apr. 15
Mississippi	Payment plan	Dec. 1	Mar. 31
Missouri	Payment plan	Nov. 1	Mar. 31
Montana	No disconnection	Nov. 1	Apr. 1
Nebraska	No disconnection	Nov. 1	Mar. 31
New Hampshire	Higher threshold	Nov. 15	Mar. 31
New Jersey	No disconnection	Nov. 15	Mar. 15
New Mexico	No disconnection	Nov. 15	Mar. 15
New York	Additional notice	Nov. 1	Apr. 15
North Carolina	No disconnection	Nov. 1	Mar. 31
Ohio*	Payment plan	mid-Oct	mid-April
Oklahoma	Additional notice	Nov. 15	Apr. 15
Pennsylvania	No disconnection	Dec. 1	Mar. 31
Rhode Island	No disconnection	Nov. 1	Apr. 15 (extended in 2011-14 & 2016-18)
South Dakota	Additional time	Nov. 1	Mar. 31
Utah	Additional notice	Oct. 1	Mar. 31
Vermont	Additional notice	Nov. 1	Mar. 31
Washington	Payment plan	Nov. 15	Mar. 15
West Virginia+	Additional notice	Dec. 1	Feb. 28
Wisconsin	No disconnection	Nov. 1	Apr. 15
Wyoming	Additional notice	Nov. 1	Apr. 30

*Ohio winter protections re-issued annually with different start and end dates.

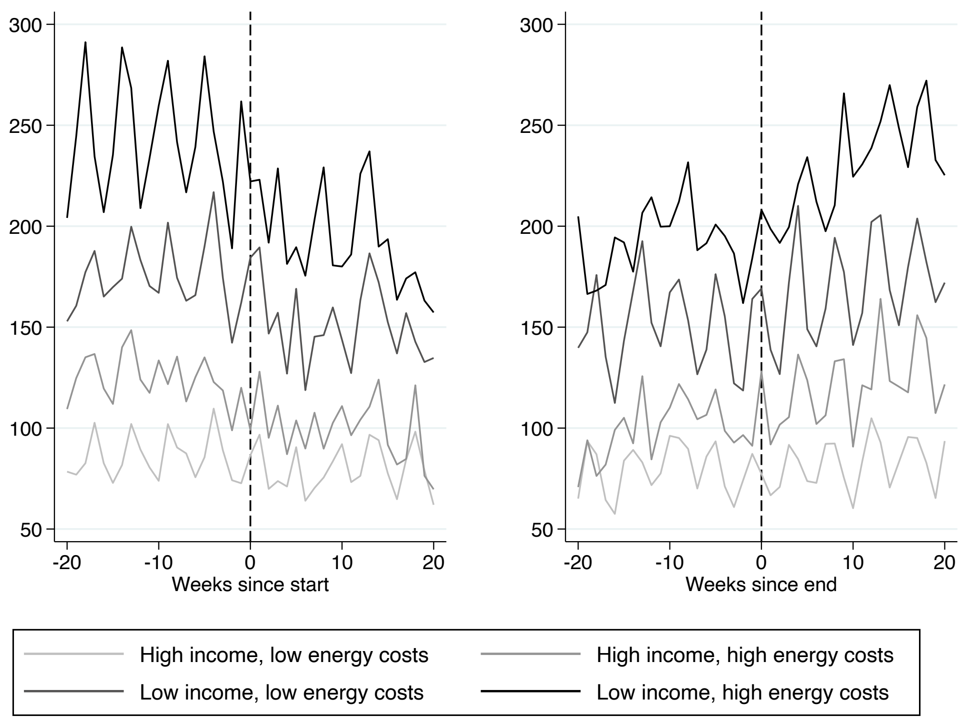
+West Virginia protected dates permanently changed to Nov. 1 - Mar. 31 in fall 2018.

Figure A1: Disconnections Example



This figure plots the raw number of monthly utility disconnections due to non-payment for four states with recent disconnection data available. For monthly disconnection reports submitted by Maryland utilities, see https://webapp.psc.state.md.us/newIntranet/test/Viewreport.cfm. For monthly disconnection reports submitted by Oregon utilities, see https://apps.puc.state.or.us/edockets/docket.asp?DocketID=21694. For monthly disconnection reports submitted by New York utilities, see https://documents.dps.ny.gov/public/MatterManagement/CaseMaster.aspx?MatterSeq=1331&MNO=91-M-0744. For monthly disconnection reports compiled by the Iowa Utilities Board, see https://iub.iowa.gov/records-information/board-reports/residential-past-due-accounts-disconnection-data. Disconnections in months with partial coverage of winter protections—meaning that the protections start or end mid-month—are depicted by a striped bar.

Figure A2: Eviction Filings per 100,000 Renter-Occupied Households



This figure plots the average eviction filing rate around the start and end of winter utility shutoff protection periods. High income corresponds to the top 50% of census tracts in my sample according to their average annual household income among renters. High energy costs corresponds to the top 50% of census tracts according to their average annual energy costs among renters.

Table A2: Temperature Endogeneity

	Dependent Variable: Active Winter Protections					
	Sample: All States			Sample: Ever-Treated States		
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Temp		-0.007***	-0.006***		-0.002***	-0.002***
		(0.000)	(0.001)		(0.000)	(0.000)
Avg Temp^2			-0.000			-0.000
			(0.000)			(0.000)
Observations	26100	26100	26100	18270	18270	18270
Adjusted R^2	0.474	0.499	0.499	0.822	0.823	0.823
Week FE	Yes	Yes	Yes	Yes	Yes	Yes

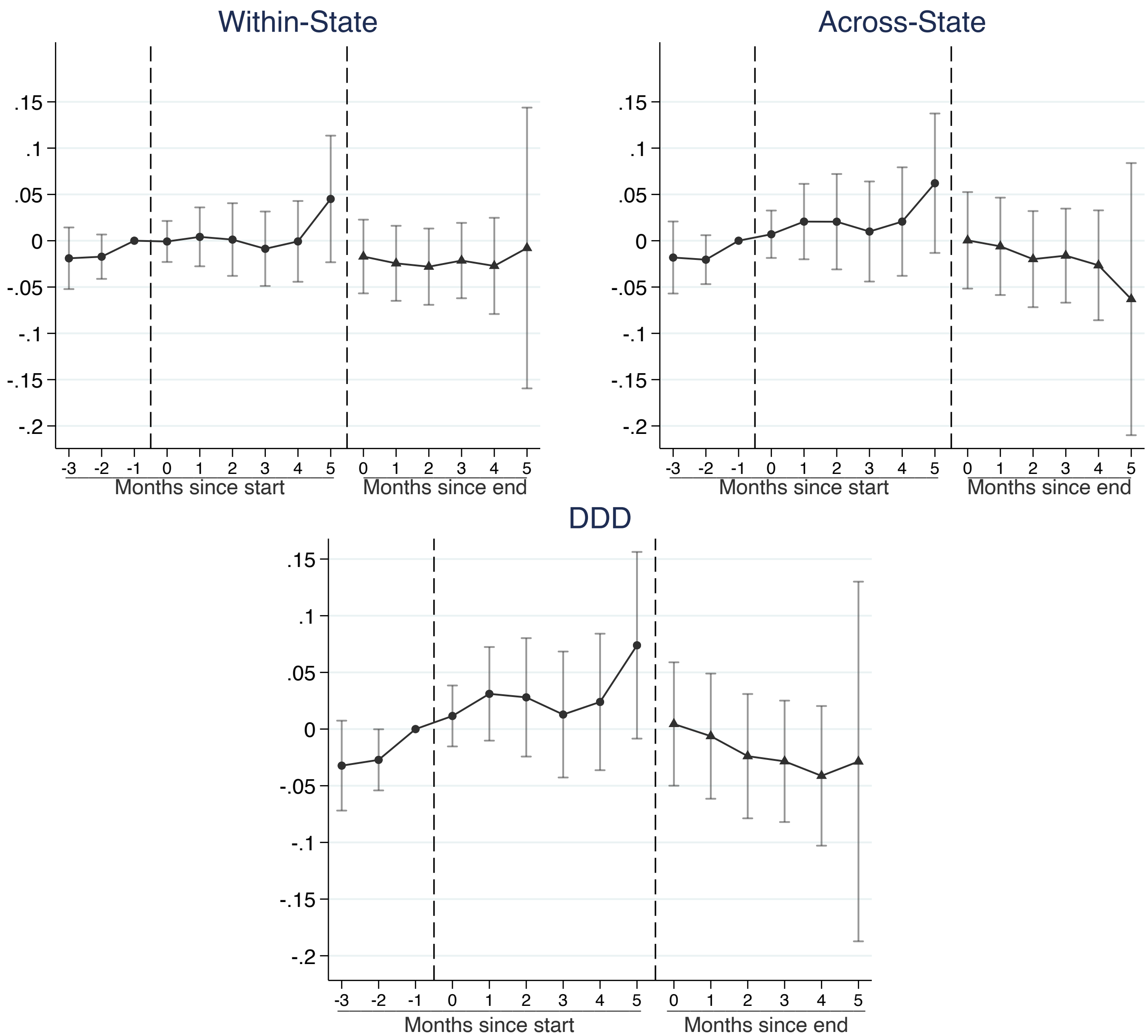
*p< 0.1, **p< 0.05, ***p< 0.01. Regression results reported in this table are derived from a state-week panel of active winter protections spanning 2010 through 2019. The temperature variables are defined as the average temperature in a state and week, measured in Fahrenheit. Heteroskedasticty-robust standard errors are reported in parentheses.

Table A3: Heterogeneous Effects by Race

	Eviction Filings per 100,000 Renter-Occupied Households		
	Within-State	Across-State	DDD
	(1)	(2)	(3)
Shutoff Protect. $\times$ High EB $\times$ $<$ 50% Non-white	-5.646	-5.037	3.042
	(4.184)	(4.686)	(4.555)
Shutoff Protect. $\times$ High EB $\times$ $\geq$ 50% Non-white	-21.37***	-14.00***	-12.76***
	(2.439)	(3.266)	(3.013)
Observations	446368	446368	446368
Adjusted R^2	0.416	0.386	0.416
Outcome Mean	159.85	159.85	159.85
Census Tract FE	Yes	Yes	Yes
Week $\times$ State FE	Yes	No	Yes
Week $\times$ High EB FE	No	Yes	Yes
Controls	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates of heterogeneous effects of winter protections on eviction filings by the race of renters in a census tract. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

Figure A3: Log Monthly Rental Payments



This figure plots monthly point estimates of the dynamic effect of winter protections on the natural log of monthly rental payments around the start and end of winter protections. The sample is restricted to renter-occupied households in the CES. Households are classified as having high energy burdens if their average gas and electric bill amounts are more than 5% of their reported income. The regressions generating these point estimates control for quintiles of household income interacted with a quadratic in average monthly temperature. Standard errors are clustered at the household level.

Table A4: Alternative Controls

	Eviction Filings per 100,000 Renter-Occupied Households					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Shutoff Protection × High EB	-9.690***	-9.436***	-9.376***	-9.738***	-9.559***	-9.365***
	(2.972)	(3.026)	(3.093)	(2.929)	(2.973)	(3.036)
Observations	446368	446368	446368	446368	446368	446368
Adjusted R^2	0.416	0.416	0.416	0.416	0.416	0.416
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × High EB FE	Yes	Yes	Yes	Yes	Yes	Yes
Income × Temp Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Poverty × Temp Ctrls	No	No	No	Yes	Yes	Yes
Temp. Form	Quadratic	Cubic	5°F bin	Quadratic	Cubic	5°F bin
Panel B						
Shutoff Protection × High EB	-9.936***	-10.20***	-9.567***	-9.704***	-9.819***	-9.439***
	(3.188)	(3.286)	(3.306)	(3.015)	(3.109)	(3.146)
Observations	446368	446368	446368	446368	446368	446368
Adjusted R^2	0.416	0.416	0.417	0.416	0.416	0.417
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	Yes	Yes	Yes	Yes	Yes
Week × High EB FE	Yes	Yes	Yes	Yes	Yes	Yes
Region × Inc × Temp Ctrls	Yes	Yes	Yes	Yes	Yes	Yes
Region × Pov × Temp Ctrls	No	No	No	Yes	Yes	Yes
Temp. Form	Quadratic	Cubic	5°F bin	Quadratic	Cubic	5°F bin

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports DDD estimates of β from Equation 1 using varying controls. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Income × temperature controls are quintiles of median household income among renters interacted with the indicated form of average weekly temperature. Poverty × temperature controls are quintiles of the poverty rate among renters interacted with the indicated form of average weekly temperature. Region dummies include the Midwest, Northeast, South and West. Standard errors are clustered at the census tract level.

Table A5: Alternative Energy Burden Definitions

	Eviction Filings per 100,000 Renter-Occupied Households		
	Within-State (1)	Across-State (2)	DDD (3)
Shutoff Protection × 2-4% EB	-6.782***	0.952	-0.00851
	(2.195)	(2.466)	(2.522)
Shutoff Protection × 4-6% EB	-17.38***	-6.358**	-5.765
	(3.129)	(3.239)	(3.506)
Shutoff Protection × 6+% EB	-28.08***	-11.23**	-8.632*
	(3.463)	(4.713)	(4.489)
Observations	446368	446368	446368
Adjusted R^2	0.416	0.388	0.417
Census Tract FE	Yes	Yes	Yes
Week × State FE	Yes	No	Yes
Week × EB Group FE	No	Yes	Yes
Controls	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates based on varying forms of energy burden among renters. The Week x EB Group fixed effects are fixed effects for the week of the year interacted with the four relevant energy burden groups. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

Table A6: Excluding Census Tracts

	Eviction Filings per 100,000 Renter-Occupied Households		
	Within-State (1)	Across-State (2)	DDD (3)
A: Exclude <2% EB Census Tracts			
Shutoff Protection × High EB	-16.80***	-12.72***	-9.132***
	(2.465)	(3.337)	(3.069)
Observations	364988	364988	364988
Adjusted R^2	0.413	0.382	0.413
Outcome Mean	177.47	177.47	177.47
Census Tract FE	Yes	Yes	Yes
Week × State FE	Yes	No	Yes
Week × HighEB FE	No	Yes	Yes
Controls	Yes	Yes	Yes
B: Exclude 0 Eviction Filing Census Tracts			
Shutoff Protection × High EB	-18.27***	-11.78***	-9.349***
	(2.404)	(3.209)	(2.994)
Observations	441948	441948	441948
Adjusted R^2	0.415	0.384	0.415
Outcome Mean	161.59	161.59	161.59
Census Tract FE	Yes	Yes	Yes
Week × State FE	Yes	No	Yes
Week × HighEB FE	No	Yes	Yes
Controls	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. Panel A reports estimates from a sample that excludes census tracts with less than 2% average energy burden among renters. Panel B reports estimates from a sample that excludes census tracts that never have an eviction filing. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

Table A7: Alternative Clustering

	Eviction Filings per 100,000 Renter-Occupied Households		
	(1) Within-State	(2) Across-State	(3) DDD
Shutoff Protection × High EB	-18.210	-12.195	-9.690
	(2.389)***	(3.164)***	(2.972)***
	{4.034}***	{6.899}*	{4.927}*
	[-27.449, -9.959]	[-26.625, -0.162]	[-20.195, -0.704]
Observations	446368	446368	446368
Adjusted R^2	0.416	0.386	0.416
Census Tract FE	Yes	Yes	Yes
Week × State FE	Yes	No	Yes
Week × High EB FE	No	Yes	Yes
Controls	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors clustered at the census tract level are reported in parentheses. Standard errors clustered at the state level are reported in braces. 90% confidence intervals derived from 999 wild-cluster bootstrap iterations are reported in square brackets.

Table A8: Effects Based on Oil Usage and Inclusion of Utilities in Rent

	Eviction Filings per 100,000 Renter-Occupied Households								
	Within-State			Across-State			DDD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Protected × Low oil	-6.312*			-13.06*			-10.34		
	(3.389)			(6.958)			(9.413)		
Protected × Pay util.		-7.043***			-6.422***			-1.507	
		(1.657)			(2.140)			(2.115)	
Protected × Either			-8.562***			-9.975***			-3.375
			(1.791)			(2.261)			(2.283)
Observations	447096	447096	447096	447096	447096	447096	447096	447096	447096
Adjusted R^2	0.412	0.412	0.412	0.383	0.382	0.383	0.412	0.412	0.412
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Week × Treat FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates using alternative definitions of treatment that are based on renters being excluded from the winter shutoff protections. Census tracts are classified as treated under the low oil definition if less than 15% of renter-occupied household have oil heat. Census tracts are classified as treated under the paying utilities definition if less than 15% of renter-occupied household have utilities included in their rent. Census tracts are classified as treated under either definition if either less than 15% of renter-occupied household have oil heat or less than 15% of renter-occupied household have utilities included in their rent. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.

Table A9: Heterogeneous Effects Based on Oil Usage and Inclusion of Utilities in Rent

	Eviction Filings per 100,000 Renter-Occupied Households								
	Within-State			Across-State			DDD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Protected × Low oil × Low EB	0.13			-2.76			-2.39		
	(3.64)			(6.77)			(9.37)		
Protected × Low oil × High EB	-21.03***			-27.35***			-23.38***		
	(4.94)			(6.85)			(8.93)		
Protected × Pay util. × Low EB		-4.61**			-3.35			0.39	
		(1.94)			(2.37)			(2.32)	
Protected × Pay util. × High EB		-9.69***			-10.29***			-4.42	
		(3.01)			(3.46)			(3.28)	
Protected × Either × Low EB			-3.88*			-4.81*			0.97
			(2.17)			(2.50)			(2.58)
Protected × Either × High EB			-15.07***			-18.24***			-9.95***
			(2.91)			(3.34)			(3.20)
Observations	446368	446368	446368	446368	446368	446368	446368	446368	446368
Adjusted R^2	0.416	0.416	0.416	0.387	0.386	0.386	0.416	0.416	0.416
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week × State FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Week × Treat FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Test Low EB = High EB									
p-value	0.00018	0.14	0.0017	0.0000062	0.063	0.00028	0.00022	0.17	0.0022

*p< 0.1, **p< 0.05, ***p< 0.01. This table reports estimates using alternative definitions of treatment that are based on renters being excluded from the winter shutoff protections. Census tracts are classified as treated under the low oil definition if less than 15% of renter-occupied household have oil heat. Census tracts are classified as treated under the paying utilities definition if less than 15% of renter-occupied household have utilities included in their rent. Census tracts are classified as treated under either definition if either less than 15% of renter-occupied household have oil heat or less than 15% of renter-occupied household have utilities included in their rent. Census tracts are classified as having high energy burdens if the average annual energy costs among renter-occupied household are at least 5% of household income. Controls include quintiles of median household income among renters interacted with a quadratic in average weekly temperature. Standard errors are clustered at the census tract level.