Out in the Cold: Effect of Temperature Shocks on Evictions

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Abstract

Almost one million households are evicted annually in the United States. The consequences of eviction can be dire, including reduced future earnings and access to credit. Understanding the drivers of eviction has thus become a pressing policy question. I use data on the near-universe of court-ordered evictions in the United States to expose an environmental cause of evictions. Specifically, I show that cold winter shocks increase eviction rates — particularly in counties that are poorer and have lower rates of White population — and hence contribute to an encroachment of poverty. I present evidence consistent with two mechanisms driving this effect. The first is energy prices: higher heating fuel prices aggravate the effect of cold temperatures on evictions. The second is a labor channel: effects are driven by counties with larger employment shares in more weather-exposed industries, such as construction and agriculture, particularly if wages in these industries experience negative growth shocks. Overall, this paper increases our understanding of how environmental shocks can exacerbate economic inequality.

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1 Introduction

> *Then her car gave out at the worst time—winter—when money was tightest. Ned had been working with a construction crew, which all but shut down in the colder months. They didn't have enough money to repair the car, and Pam lost her job. That's when they fell behind with Tobin.* [...] *Lorraine had used $150 of her rent money to pay a defaulted utility bill with the hope of having her gas turned back on. She wanted to take a hot shower, scrub away the smell. She wanted to feel clean, maybe even something closer to pretty.*
>
> Quotes in Desmond (2016), documenting the story of families that underwent eviction

More than 2 million households are estimated to be served an eviction order per year in the United States, with approximately half of those actually facing eviction (Desmond et al., 2018b). Evicted households experience an increased rate of homelessness, and have lower future earnings and credit access. These effects are particularly acute for Black and female tenants (Collinson et al., 2021). Moreover, evictions come with a legal record, which further limits the future housing choices of these households (Desmond, 2020).[1] Hence, evictions might lead already impoverished households beyond a tipping point from which it would be increasingly difficult to recover.

Understanding what drives households towards eviction has become a pressing policy question, as more local authorities in the United States are determined to curb increasing eviction rates (Humphries et al., 2019). Even as the consequences of evictions become better known (Collinson et al., 2021), there are still gaps in our understanding of the causes that lead some households towards eviction, while others are spared (Desmond and Gershenson, 2017).

This paper exposes an environmental driver of evictions. Specifically, I show that relatively small cold weather shocks during the winter increase the rate of households who are served an eviction order and are finally evicted. I document two main mechanisms behind this main result. The first is energy poverty: the effect of cold winters on evictions is higher when natural gas prices rise, consistent with anecdotal evidence of credit-constrained households having to choose between paying rent or utility bills during winter. The second is labor shocks: the effect of cold winters on evictions is concentrated on counties with a higher percentage of the labor force in more weather-exposed industries—natural resources and mining, construction, and manufacturing—specially so when wages experience plausibly exogenous negative growth shocks. Overall, this paper provides evidence of a channel through which environmental factors impact economic inequality. Moreover, these findings shed light on the sort of environmental policies—such as lower fuel taxes during the winter season—that might curb the relationship between cold temperatures and evictions.

[1] For instance, households with an eviction order in their record cannot qualify for public housing (Desmond, 2020).

To arrive at these results, I use panel data on the near-universe of eviction filings and evictions in the United States in the period after the Great Recession (2010-2016), constructed by Desmond et al. (2018b). These data include all recorded court-ordered evictions in the United States, and it is the most comprehensive dataset of evictions at the federal level to date (Hepburn and Panfil, 2021). I combine these eviction data with winter temperatures at the county level. Specifically, I use data from Schlenker (2020), which include minimum and maximum daily temperatures on a 2.5x2.5 mile grid coming from a balanced panel of weather station records. With these data, I construct Heating Degree Days (HDD) over each county in the continental United States at the season level. HDD are a measure of the coldness of a place[2], and are a common metric to estimate energy demand for heating (EIA, 2020). Rather than relying on the most common approach of using average daily temperatures to estimate HDD,[3] I take into account parts of days that were below the reference temperature of 18°C (65°F). So, my constructed HDD measure represents the coldness felt at any point during the winter season by the population of a county.

Exploiting random variation in the number of HDD during winter within counties across years in a fixed effects model, I find that 100 more HDD (approximately half of the standard deviation within counties during the study period) increase evictions filings by 3% and evictions by 2%. The effects of HDD are concentrated in the winter season, as more HDD during the preceding fall or following spring do not significantly change the rate of evictions or filings. I also show that the impacts of cold winters on evictions can be delayed: experiencing 100 more HDD during the winter of a certain year increases the rate of eviction filings one year later by 2.7% and two years later by 3.6%.[4] Finally, I find that these effects are concentrated on counties that are poorer, have a lower percentage of White population, and a lower median property value.

I then explore what mechanisms might be behind colder winters causing higher eviction rates, and find evidence consistent with two main channels. First, using a shift-share instrument, I document that positive shocks in national natural gas prices increase the effect of HDD on eviction rates on counties that use more natural gas as heating fuel. This finding is consistent with anecdotal evidence of credit-constrained households having to choose between paying rent or utility bills during winter (Desmond, 2016).[5] On the other hand, I

[2]Specifically, in a graph that plots the evolution of temperatures over time, HDD measures the area below the 18°C ordinate and above the temperature curve.

[3]For instance, HDD estimates by NOAA (2012) rely on average daily temperatures to classify one whole day as a HDD or not, and hence, do not consider parts of the day that might have been below the threshold temperature.

[4]Testing the null-hypothesis that winter HDD on a given year, the year prior, and two years prior have jointly no effect on filings is smaller than 0.001, and equal to 0.002 for evictions.

[5]In the context of California, Auffhammer and Rubin (2018) also find that low-income households are more elastic to natural gas prices during winter than high-income households, while all households are inelastic to prices during the summer months.

do not find evidence of electricity prices modulating the effect of HDD on evictions. I posit this could be due to the more stable electricity prices during the period.[6] Second, I find that the effect of winter HDD on evictions is driven by counties where a higher percentage of their labor force works in goods-producing industries,[7] which are traditionally identified as climate-sensitive industries (Addoum et al., 2019; Graff Zivin and Neidell, 2014; Behrer and Park, 2017). When wages in these sectors experience a positive aggregate shock, the effect of winter HDD on eviction rates *decreases* in absolute value in these counties. This finding would be indicative of colder winters constraining household budgets for laborers of goods-producing industries, who are then less likely to be able to afford rent (Desmond, 2016).

Finally, I explore whether existing pro-tenant policies are correlated with differential impacts of winter HDD on evictions. First, I investigate the effects of state landlord-tenant regulations leaning pro-landlord or pro-tenant—using two ranking systems, one developed by legal analysts at RentCafe (Brasuell, 2018) and another by Benfer et al. (2020b). I find that colder winters do not significantly impact eviction filings or evictions in states whose landlord-tenant regulations are more pro-tenant. The effects are instead driven by more pro-landlord states. Second, I find that the effect of winter HDD on evictions is actually *higher* in states that have implemented regulation to ban utility disconnections under certain conditions (during winter time, or if temperatures fall below a threshold), than in states without those regulations. This could be due to reverse causality: states with higher rates of disconnections and evictions implementing more measures to protect tenants. But, this finding would also be consistent with evidence that temporal bans on utilities disconnections do not reduce evictions nor disconnections, it merely displaces them in time (Cicala, 2021; Desmond, 2016).

Overall, this paper advances our understanding of how environmental shocks increase economic inequality. Evictions lead almost one million households per year in the United States to a situation in which they are more likely to become homeless and have lower future incomes. I show evidence that cold weather shocks drive more households into eviction, and hence, contribute to an encroachment of poverty. Given the two main mechanisms identified, this paper also sheds light on potential policy avenues that can help curbing increasing eviction rates. Specifically, alleviating energy poverty—for instance, through lower fuel taxes during the winter season—or providing larger benefits for workers of weather-exposed industries during cold winters might be particularly effective.

[6]During the study period (2010-2016), the standard deviation of the annual growth rate of natural gas prices was five times that of electricity prices.

[7]These are industries classified with a NAICS supersector code equal to 06, and include: natural resources and mining, construction, and manufacturing.

Contribution to the literature. This paper contributes to several strands of the literature.

First, this paper speaks to the literature evaluating how environmental outcomes impact economic inequality. A growing body of work explores distributional impacts of environmental policies, such as cap-and-trade (Fowlie et al., 2012; Grainger and Ruangmas, 2017; Hernandez Cortes and Meng, 2020; Shapiro and Walker, 2021), air emissions regulation (Currie et al., 2020), or clean-up of hazardous sites (Gamper-Rabindran and Timmins, 2013). A related literature explores how environmental shocks might strengthen inequality, frequently in the context of climate change (Diffenbaugh and Burke, 2019; de Laubier-Longuet Marx, 2018), or natural disasters (Kahn, 2005; Kellenberg and Mobarak, 2008; Lackner, 2019; Varela Varela, 2019). Hsiang et al. (2019), Ma et al. (2019), and Banzhaf and Timmins (2019) review these broad literatures. This paper illustrates a novel mechanism through which environmental shocks can affect economic inequality. The comprehensive dataset on evictions I use allows me to provide new evidence on how temperature fluctuations impact the rental sector, which houses the families with the lowest incomes in the United States. Evictions can contribute to an encroachment of poverty, by leading already distressed households—specially Black and female-headed—beyond a tipping point after which lower access to credit and future earnings might make it difficult to bounce back. Hence, this paper improves our understanding on the environmental roots of evictions, which is important to prevent some of the most destitute households in the United States falling deeper into poverty.

Second, I contribute to the literature that investigates the consequences of energy poverty and insecurity (EU Energy Poverty Observatory, 2017). Even if a large part of this literature focuses on developing country settings (González-Eguino, 2015), there is a growing body of work documenting the health consequences of households inability to meet energy needs in developed countries (Chirakijja et al., 2019; Churchill and Smyth, 2020; He and Tanaka, 2019). In the United States specifically, recent research has highlighted how energy-poor households facing utility disconnections are more likely to be low-income and minority (Cicala, 2021; Graff and Carley, 2020). This paper moves beyond health and mortality outcomes to present further evidence of the welfare consequences of energy poverty. I show that high heating fuel prices, combined with cold winter shocks, increase the rates of eviction. By doing so, I provide further empirical support to calls for energy prices to be more equitable and progressive (Borenstein et al., 2021). Specifically, I show evidence that lowering fuel taxes during winter—as suggested by Auffhammer and Rubin (2018) in the context of California—might increase the equity of the tax burden.

Finally, this paper also contributes to the scarce economics literature on evictions. A recent paper by Collinson et al. (2021) focuses on the consequences of evictions—in the context of New York City and Cook County, Illinois, where Chicago is located.[8] This paper provides causal evidence that evictions reduce earnings, credit access, and durable goods consumption, and hence builds upon the ample body of work in the anthropology, sociology, and public health literatures that document the dire consequences associated with evictions—including increased homelessness, mental health deterioration, and job loss (Desmond, 2016; Desmond and Bell, 2015; Greiner et al., 2012; Phinney et al., 2007; Vásquez-Vera et al., 2017). The literature on the causes of evictions is more sparse. One notable example is Desmond and Gershenson (2017), which find that, among other factors, large family size and job loss are correlated to future eviction in the context of Milwaukee. I provide novel evidence on environmental causes of evictions at the national level. This evidence then increases our understanding on the causes that drive some households towards eviction, and hence the poverty trap that could follow. By doing so, this paper helps elucidate what sort of policies—such as lower fuel taxes during the winter season, or larger benefits for workers of climate-sensitive industries during cold winters—might mitigate eviction rates.

Paper outline The remainder of the paper proceeds as follows. Section 2 provides a brief background on how evictions are initiated and processed in the United States. Section 3 describes the data, and section 4 details the empirical models used to analyze them. Main and heterogeneous results are summarized in sections 5 and 6, respectively. Section 7 presents evidence of mechanisms that operate the main effect. In Section 8, I present an exploratory analysis of whether existing pro-tenant policies are associated with changes in the main effect identified. Section 9 concludes.

2 Background

This section provides background information on the eviction process in the United States.

Eviction rates in the United States have been increasing steadily in the past few decades. Desmond (2016) describes how evictions were so rare in the 1930s and 1940s that they drew crowds when they were been executed. Nowadays, evictions have become so common that there are moving companies specializing in evictions and law-enforcement squads uniquely devoted to execute evictions and foreclosures. During the study period of this paper, 2010-2016, an average of 2.3 million evictions were ordered every year in the continental United States, with 0.9 million of those resulting in evictions annually (Desmond et al., 2018b). These figures translate into 2 households being evicted every minute in the United States on average. This rise in evictions has been attributed to stagnant incomes and rising utility

[8] Previously, this working paper was presented as two, Collinson and Reed (2018) and Humphries et al. (2019), which analyzed data just from New York City and Cook county, respectively.

and housing costs[9] (Desmond, 2020), resulting in a quarter of families below the poverty line devoting more than 70% of their income to rent (Desmond and Bell, 2015). In the past decade, the rise in corporate landlordship—originated by investors acquiring properties that had been foreclosed during the financial crisis of 2008-2009—has also been faulted with increasing eviction rates, as corporations have been found more likely to evict tenants than smaller landlords (Klinger, 2020; Raymond et al., 2016).

An eviction takes place when a landlord expels a tenant from a residence. Most evictions result from defaults on rent payment, and fewer are associated to other causes (lease violations, property damage, etc.) Evictions can be carried out formally through the court system, or informally (through illegal lock-outs, for instance.) Specific procedures to carry out formal eviction processes vary by jurisdiction. This generates substantive variation across the United States on, for instance, whether an eviction process must start with an out-of-court termination notice; the period of time landlords have to wait to file for eviction after written notice was handed; whether a reason has to be given for eviction; etc.[10] (Desmond et al., 2018a). Specifically, there are no federal regulations against evictions during winter in the United States, although there exist some municipal-level cold weather eviction bans.[11]

Formal evictions are usually heard in civil courts at the county-level (Desmond et al., 2018a). The process from filing to the resolution of an eviction case can take several months, although then hearings are usually concluded very quickly.[12] The vast majority of tenants in these hearings do not have legal representation, although most landlords do (Desmond and Bell, 2015). Eviction cases are resolved in mostly three ways: with an eviction judgement (tenants must vacate the property), dismissal (tenants can remain the property), or with a mediated agreement (landlord and tenants agree on terms of payment, which halt eviction if satisfied.)

3 Data: sources and processing

This section describes the data used in this paper, specifically, those employed to construct the main dependent and explanatory variables: evictions and temperatures. It outlines how these data were processed to obtain relevant variables, and summarizes key statistics.

[9] Since the late 1990s, median rent has increased by 70%, and the cost of fuels and utilities by over 50% (Desmond and Bell, 2015), while real wages have not changed significantly—particularly for workers with the lowest wages (Desilver, 2018).

[10] In section 8, I explore whether more pro-tenant of more-landlord state landlord-tenant regulations affect the main results in this paper.

[11] For instance, in Chicago, there are no evictions executed during Christmas week, or if temperature falls below 15°F. In Washington DC, evictions are halted if temperatures are below 32°F, or if there is more than a 50% chance of precipitation (Holder, 2017)).

[12] Humphries et al. (2019) describe how eviction hearings are completed in less than 2 minutes in average in Cook County, Illinois, an area that includes Chicago.

Evictions The main dependent variables of interest, evictions and eviction filings per year and county, come from the database constructed by Desmond et al. (2018b). These data summarize the near-universe of recorded court-ordered residential evictions in the United States, and constitute the most comprehensive dataset of evictions at the federal level to date (Hepburn and Panfil, 2021). More details on how these data were compiled and processed are summarized in Desmond et al. (2018a).

The dependent variables used from this dataset are eviction $filings$, which count all eviction cases filed in a county in a year, and *evictions*, which are the number of eviction cases that resulted in a tenant ordered to vacate a property in a given in a year. As described in section 4, both variables are entered in the empirical models in log form. This paper analyzes eviction in the period after the Great Recession (2010-2016).[13]

Descriptive statistics of filings and evictions are summarized in the last two rows of table 1. On average, there were 885 eviction filings annually by county (within-county standard deviation: 457) and 375 evictions (within-county standard deviation: 279). These data were originally constructed from eviction records stored in county courts, so their availability varies by county. However, figure 1, that plots the spatial variation of filing and eviction rates during the study period, shows that these data cover most of the US.[14] Despite its comprehensiveness, there is no data on evictions available for the states of Arkansas, North Dakota, and South Dakota. Data on New York state is also sparse, given how eviction data is recorded.[15] With respect to temporal coverage, the majority of counties (around 82 %) have filings and evictions observations for every year of the study period.[16] In any case, robustness checks in section 5 show that the main result is robust to limit the sample to a balanced panel of counties that are not missing data in any year of the period.

Finally, because this dataset only includes court-ordered evictions, I am not able to analyze $informal$ evictions, that is, those that are executed without initiating a legal process. As a consequence, the effect of cold weather shocks on evictions I document is likely a lower bound, given that effects on informal evictions are not included in the estimation.

Heating Degree Days (HDD) I construct the main explanatory variable of interest, Heating Degree Days (HDD), using data from Schlenker (2020). This dataset contains minimum and maximum daily temperatures on a 2.5x2.5 mile grid over the continental US. Impor-

[13]Evictions have arguably become more professionalized in the aftermath of the Great Recession. The rate of corporate homeownership increased during the 2010s, as investors acquired properties that had been foreclosed during the financial crisis (Klinger, 2020). These corporate landlords have been found to be more likely to evict their tenants than smaller landlords (Raymond et al., 2016).

[14]As shown on table 1, the dataset contains at least one filing observation through the period for 2,827 counties in the continental US; and at least one eviction observation for 2,643 counties.

[15]In New York state, evictions are only in the public record if the plaintiff (landord) pays to place them there (Desmond et al., 2018a).

[16]Out of a total of 7 years, the average temporal coverage by county is 6.7 year for filings, and 6.6 for evictions.

tantly, these data are derived from a balanced panel of weather stations—unlike other commonly used datasets that contain gridded temperature, such as PRISM (PRISM, 2019). That is, temperature readings come from a fixed set of weather stations. If one station in this set is missing data on a particular day, Schlenker (2020) uses an interpolation technique to fill the gap. With an unbalanced panel, missing data on certain stations during some periods of time would add noise to the data. Given that I use a fixed effects model for identification (as described in section 4), this noise would be amplified as the fixed effects absorb average temperatures, which could bias estimates.

I then construct HDD from those daily minimum and maximum temperature readings. HDD are a commonly used metric to estimate energy demand for heating (EIA, 2020). Specifically, in a graph that plots the evolution of temperatures over time, HDD measures the area below a chosen temperature threshold and above the temperature curve. I use 18°C—approximately 65°F—as the reference temperature, which is the threshold typically used in the United States (Martínez et al., 2019).

To construct HDD, I assume that daily temperatures vary linearly between the recorded minimum and maximum values. Then, for each point in the grid, I evaluate when and by how much temperatures were below 18°C at any point in the day. Then, I average all grid-points that fall within the boundaries of a county to obtain daily HDD for that county.[17] The final winter HDD variable used in the analysis aggregates all daily observations during the winter season (defined as the months of January, February, and March.) By considering partial days below the threshold temperature, I assess the coldness felt at any point during the winter season by the population of a county more precisely than the HDD estimates commonly used.[18]

The first row of table 1 contains the descriptive statistics of the final HDD variable, and figure 2 plots the spatial distribution of average and standard deviation values. Overall, a county experiences an average of 1,382 HDD during winter (within-county standard deviation: 183 days.) To obtain more easily interpretable estimates, I scale the HDD variable to represent 100 HDD. Hence, the main explanatory variable can be understood as approximately half of a within-standard deviation ($100/183 \approx 0.55$).

Other data Other data sources, notably those used to evaluate heterogeneous effects and mechanisms, are summarized in table A.5. All baseline variables noted on that table (including demographics and county shares by fuel type, industry, and causes of mortality) are measured on 2009 or prior, so they are not possibly affected by future HDD. All mone-

[17] As a robustness check, I also compute HDD for a county using grid points that fall within urban areas, as defined by the Census.

[18] For instance, HDD estimates by NOAA (2012) rely on average daily temperatures to classify one whole day as a HDD or not, without considering times of the day when temperature might have fallen below 18°C.

tary values have been normalized to reflect year 2020 dollars.

4 Empirical Strategy

This section describes and justifies the specifications I use to analyze the effect of cold winter shocks on filings and evictions, as well as to explore potential mechanisms.

Main fixed effects model I exploit random variation in the number of heating degree days within counties across years to identify the effects of cold winter shocks in filings and evictions. Equation 1 presents the main fixed effects model:

$$y_{csy} = \beta \cdot HDD_{csy} + \mu_{cs} + \delta_{sy} + \varepsilon_{csy} \tag{1}$$

The dependent variables of interest, y_{csy}, are the total eviction filings (in logs) or evictions (in logs) in county c of state s in year y. HDD_{csy}, the main explanatory variable, measures heating degree days (in hundreds, computed as described in section 3) during the first quarter of year y in county c of state s. The model also includes county fixed effects, μ_{cs}, to control for unobservables that are time invariant within counties; and state-year fixed effects, δ_{sy}, to absorb common shocks to all counties in state s during year y. Given that evictions are usually heard on civil courts at the county level (Desmond et al., 2018a), I allow standard errors, ε_{csy}, to be correlated within counties.

The model in equation 1 links winter temperatures with filings and evictions that happen throughout the year (so, not only during winter, but also later in the year.) This is due in part to the temporal resolution at which the eviction data is available. However, it is also intuitive that filings do not respond immediately to a negative temperature shock. For instance, depending on the operating mechanism, a cold weather shock might make a tenant default on rent weeks or months after it happened. Then, and depending on the relevant jurisdiction, landlords might have to wait a period of time after non-payment before being able to file for eviction. The potential lag between shock and outcome might be particularly salient in the case of evictions, as the process between filing and eviction order can span several months (as described in section 2.)

The coefficient of interest in model 1 is β. If the hypothesis that colder winters (that translate into more HDD) lead to a higher rate of filings and evictions, β would be positive and significant.

Extensions of the main model In some extensions of the main model, I add time-variant controls to equation 1. First, I include the number of HDD during the preceding fall and following spring season, to allow the effect of cold weather shocks to be distributed throughout the year. Second, I control for one- and two-year lags of HDD, to allow for the effect of cold winter shocks on evictions to be delayed beyond one year. Third, I control for one-year lag of the dependent variable (either filings or evictions). The lagged dependent variable is not biasing β, as it is orthogonal to current HDD. However, I expect the lagged dependent variable to be a strong predictor of current values, which would increase the precision of the estimation of β. Fourth, I include a quadratic polynomial in total precipitation in county c, to account for the fact that changes in annual precipitation could be correlated both with HDD and filings and evictions, and hence omitting precipitation could be biasing β.

Temperature bins The specification in equation 1 assumes a linear relationship between HDD and evictions. Hence, it assumes, for instance, that the effect of one day spent at 0°C is equivalent to 2 days spent at 9°C.[19] To allow more flexibility on how cold winter temperatures impact evictions, as well as to explore non-linearities in the relationship between temperatures and evictions, I substitute the main independent variable in equation 1 by a set of variables summarizing total time—including partial days—that county c spent in 10°C temperature intervals. Time spent below -10°C (14 °F) is lumped together in one variable, as well as time spent above 20°C (68 °F). Equation 2 presents the resulting model. The omitted category is the (10°C, 20°C) interval, which includes the reference value of 18°C used to compute HDD. Then, the β_i coefficients in equation 2 measure the average impact of spending one more day in a certain temperature interval with respect to spending one more day in the (10°C, 20°C) interval.

$$y_{csy} = \beta_1 T(< -10)_{csy} + \beta_2 T(-10, 0)_{csy} + \beta_3 T(0, 10)_{csy} + \beta_4 T(> 20)_{csy} + \mu_{cs} + \delta_{sy} + \varepsilon_{csy} \quad (2)$$

Mechanisms: shift-share instrument Finally, I use the specification described in equation 3 to evaluate how potential mechanisms (notably fuel prices and wages in goods-producing industries) modulate the relationship between HDD and evictions. Both local fuel prices and wages could potentially be correlated with filings and evictions and HDD in a county. Hence, to achieve plausibly exogenous variation, I substitute these variables by two shift-share types of instrument. In the case of natural gas, for instance, this variable is composed of the interaction between the percentage of households that use natural gas as heating fuel in county c at baseline (the *share*) and the national average growth in natural gas prices during year y (the *shift*). Intuitively, this instrument exploits that common variation in natural gas prices differentially affects the relationship between HDD and evictions in each county

[19] This equivalence comes from the way in which HDD are computed, as described in section 3: in a graph that plots the evolution of temperatures over time, HDD measures the area below the 18°C ordinate and above the temperature curve.

based how many households use natural gas for heating in that county.[20] I use a similar approach to test whether labor force in climate-sensitive industries might be a potential mechanism. In that case, the percentage of the labor force working in climate-sensitive industries in county c at baseline is the *share*, while national average growth in wages in those industries in year y is the $shift$.

$$y_{csy} = \beta \cdot HDD_{csy} + \theta \cdot HDD_{csy} \cdot share_{cs} \cdot shift_y + \alpha \cdot HDD_{csy} \cdot share_{cs} + \gamma \cdot HDD_{csy} \cdot shift_y + \delta \cdot share_{cs} \cdot shift_y + \mu_{cs} + \delta_{sy} + \varepsilon_{csy} \quad (3)$$

The coefficient of interest in model 3 is θ. To illustrate, in the case of natural gas, a positive and significant θ would imply that the effect of HDD on evictions is increased in counties which use natural gas as heating fuel when natural gas prices are higher. It will be indicative of higher fuel prices *worsening* the effect of HDD on evictions.

Interpreting θ in a causal sense in these models would require that the *share* variables—i.e. county shares by fuel type and by industry—do not predict changes in filings and evictions other than through the $shift$ variables—i.e. national average growth of fuel prices and wages, respectively. One way to assess whether this is a sensible assumption is to look at the correlates of the *share* variables (Goldsmith-Pinkham et al., 2020). Hence, in each case, I analyze the correlates of the relevant share variable with other observables.

5 Main result: evictions increase with cold weather shocks

This section summarizes the key result of this paper: evictions filings and evictions increase with cold weather shocks. I first present results using heating degree days (HDD) as a dependent variable. Then, I allow for more flexibility on how temperature affects evictions, and model temperature in 10°C bins. Finally, I show that these results are robust to alternative specifications.

Dependent variable: Heating Degree Days Table 2 summarizes the impacts of HDD (measured in hundreds) on eviction filings (panel A, top) and evictions (panel B, bottom) analyzed with the model described in equation 1 in section 4.

Column 1 shows that 100 more HDD (approximately half of the standard deviation within counties during the study period, as shown in table 1) increase eviction filings by

[20] Chirakijja et al. (2019) use a similar model in a recent working paper. They focus on different outcomes and treatments of interest from those of this paper. Specifically, they are interested in evaluating the effects of fuel prices on mortality. To instrument for prices, they interact the share of households that use natural gas for heating with the ratio of natural gas and electricity national prices. They then further interact this variable with HDD to gain more variation on fuel demand.

3% and evictions by 2%. The results for evictions are noisier, and this model without additional controls yields a relatively large p-value (0.13). Including a quadratic polynomial in total annual precipitation (column 2) does not change the main results for either filings or evictions, evidencing omitting precipitation from the main model was not biasing these results.

Column 3 summarizes results of including one-year lag of the dependent variable as a control. As expected, the coefficients on HDD do not change: as current HDD and lagged evictions and filings are orthogonal, the lagged variables were not introducing bias. However, lagged variables are strong predictors of the dependent variables, showing that past and current evictions and filings are positively correlated within counties. As a result, adding lagged dependent variables as controls improves the precision of the estimation for the HDD coefficient. In the case of evictions, the p-value of the estimate drops to 0.09.

Column 4 analyzes the impact of HDD during other seasons. Results in this column show that HDD during the preceding fall and following spring seasons both have positive point estimates in the case of filings, but are not individually significantly different from zero. However, the p-value of testing that the coefficients of HDD during fall, winter, and spring are all jointly equal to zero is equal to 0.009, showing a significant effect of HDD during the coldest months of the year on filings. Results for evictions are noisier (p-value of joint null hypothesis is 0.17.)

Finally, columns 5 and 6 explore whether the effect of HDD on evictions and filings is delayed. 100 more winter HDD increase filings by 2.7% on the following year, and by 3.6% two years later. The effect of adding lags of winter HDD is even stronger in the case of evictions. Testing the null hypothesis that the coefficients of current, one-year, and two-year lag HDD are jointly equal to zero is 0.002 for evictions. It makes intuitive sense that filings respond quicker to a shock than evictions themselves, given that the latter are the result of potential long judicial processes, as described in section 2.

Cooling Degree Days These documented impacts of cold weather shocks during winter on evictions and filings raise the question whether there could be a similar effect of hot weather shocks during summer (when heat waves might lead to higher energy use for air conditioning, for instance.) I use the same model in equation 1 and the same dependent variables—filings and evictions—but I substitute HDD for Cooling Degree Days (CDD) as the main explanatory variable. CDD are an equivalent metric to HDD[21], but to represent *high* temperatures in a place. CDD are then indicative of the demand for cooling.

Table A.3 presents the results of this analysis. It shows that that the effect of hot summers on both evictions and filings is not distinguishable from zero. The effect of more CDD during

[21] In a graph that plots the evolution of temperatures over time, CDD measures the area *above* the 18°C ordinate and *below* the temperature curve.

winter and spring is likewise not significant. However, the coefficient for the fall is negative and significant for both evictions and filings. That is, warmer fall seasons decrease the rate of evictions and filings. This result provides further evidence of the main result of this paper: a mild cold season decreases the rate of evictions and filings.

Exploring non-linearities: Temperature Bins To allow more flexibility on the relationship between temperatures and evictions (including non-linearities), I substitute the aggregate HDD variable in the main model in equation 1 by a set of temperature-bins variables. These variables summarize total time—including partial days—that county c spent in 10°C temperature intervals during the winter of year y.

Figure 3 summarizes the point estimates and 95% confidence intervals of running this model, with filings as a dependent variable in the top panel, and evictions in the bottom panel. The omitted category in both models is the (10°C, 20°C) interval, which includes the reference value of 18°C used to compute HDD. These results show that spending one more day below -10°C increases filings and evictions by approximately 1 percentage point more than one more day in the (10°C, 20°C) interval. The point estimate of one more day in the (-10°C, 0°C) interval is slightly smaller (0.5 percentage points for filings, 0.8 for evictions). But, given the confidence intervals of these estimates, I cannot rule out that the estimates for the coefficients of the $< -10°C$ and (-10°C, 0°C) intervals are equal. Hence, these results reject the existence of non-linearities in the relationship between temperatures and evictions, and support the use of the linear HDD measure in the main model.

Robustness Table A.1 shows that main results are robust to changes in the definition of the explanatory variable, to changes in the sample, and to the specification of the standard errors.

First, I modify the explanatory variable so it only measures HDD over urban areas—where population, and hence evictions and filings, are concentrated—rather than the whole area of a county. Because of the heat island effect (EPA, 2014), urbanized areas can be significantly warmer than surrounding areas, which might induce a wedge on HDD measured over urban areas or the whole county. Column 1 of table A.1 shows however that the main result is robust to this change of the explanatory variable.

Second, I explore robustness to changes in the sample. Desmond et al. (2018a) flag that some of the evictions and filings data might have certain issues. These are observations that were imputed rather directly observed, i.e. averaged across years if only one data for one year was missing (1% of the sample); pulled from secondary sources (8% of the sample), or estimated to be lower counts of the actual eviction and filings cases (22% of the sample). Removing all those flagged observations does not alter the results (column 2); indeed, the point estimate of the HDD coefficient is slightly larger. Moreover, column 3 shows that results remain unchanged if the sample is limited to a balanced panel, that is, including only counties without any missing data on filings and evictions during the study period.

Finally, the last three columns of table A.1 allow for different correlation structure of the standard errors, by clustering them by state (column 3), county×year (column 3), and double-clustered standard errors at the county and year levels (column 5). All coefficients remain significant at least at the 10% level.

To allow for even more flexibility in the structure of serial and spatial correlation of standard errors, I follow the approach in Conley (1999) with code developed by Hsiang (2010) to allow errors to be correlated both spatially (within a certain spatial cutoff) and temporally (within a certain lag.) Besides serial correlation, this structure allows observations from counties that are arbitrarily close to be correlated. Table A.2 shows the standard errors of the HDD estimate in the main model[22] with different spatial cutoffs (from 100 to 2000 km), and temporal lags (from 1 to 5 years.) The coefficient of HDD remains significant at least at the 10% level for all pairwise combinations of cutoffs and lags.

6 Heterogeneity: by baseline demographics and average winter temperatures

This section explores heterogeneity in the main result presented in the previous section according to baseline demographics and underlying local climate. I show that the effects of cold weather on evictions are driven by counties with lower percentages of White population, lower property values, higher poverty rates, and higher average winter temperatures.

Baseline demographics I analyze whether there is heterogeneity in the main result according to three demographic characteristics of counties: percentage of population that identify as White, median property values, and share of households with incomes below the poverty line. To explore heterogeneity, I divide the counties in the main sample into two subsets for each of the variables I analyze. Each county is assigned to a subset according to whether its baseline value of each variable is above or below the sample median.[23] I then run the main model in equation 1 (without controls) in each of the subsets of the data.

Figure 4 presents the results of these analyses. It shows that the effect of HDD on filings is positive and significant at the 1% level for counties *below* the median percentage White population and property value; and *above* the poverty rate median. On the other hand, the

[22]Main model as defined in equation 1, including the lagged dependent variable and a quadratic in precipitation as controls. Results from this main model are summarized in column 3 of table 2.

[23]For the socioeconomic demographics, baseline values are computed as the county averages of the values reported in the 2000 Census and the 2009 5-year American Community Survey. For HDD during winter, I compute the average of winter HDD during 2000-2009.

effect of HDD on filings is not significantly different from zero in counties above the median of percentage White and poverty rate, and below the property value median.

These results are suggestive of the effect of cold winter shocks on eviction filings being driven by less White and poorer counties. Even if these findings point out to heterogeneity along the lines documented in the literature (evictions more commonplace in poorer, less White counties (Desmond, 2012)), I cannot rule out that the values above and below the median for each of the variables are actually equal. That is, given the precision with which I can evaluate the point estimates, the resulting p-values of testing their differences are all larger than 0.1.

Average winter temperatures Figure 4 also shows that the effect of HDD on filings is positive and significant at the 1% level for counties that are *warmer*, that is, whose baseline average winter HDD is below the median. For counties with colder winters on average, I cannot rule out that the effects of temperatures on filings is actually zero. (Although again, the difference between the coefficients is not itself significant: p-value is 0.3.) This result could be consistent with a pattern of adaption: population of colder counties on average expect and are more prepared to face cold weather shocks, and hence, random shocks of HDD do not affect evictions. However, counties which are warmer on average also tend to be poorer, with less percentage Whites, and lower median property values (as it can be seen in figure 5, that plots a correlation matrix between these variables). It could be that the effect of these demographic characteristics is driving the effect of HDD on evictions in warmer counties.

7 Mechanisms: heating fuel prices, labor shocks, and cardiovascular and respiratory mortality

This section explores three potential mechanisms through which cold weather shocks could lead to a higher rate of evictions. First, I show that the positive effect of cold weather on evictions is aggravated by high natural gas prices. Second, effects are driven by counties with a large proportion of workers in industries more susceptible to the weather, specially so when wages in these industries are low. Finally, I also show that these effects are concentrated on counties with a higher baseline rate of mortality due to cardiovascular and respiratory diseases.

Heating fuel prices I start by analyzing whether heating fuel prices could be a channel through which cold weather shocks lead to more evictions. Evidence of this channel would be consistent with anecdotical evidence that credit-constrained households might have trouble paying both rent and utility bills during winter (Desmond, 2016). This struggle would be higher if winters are colder or energy prices are higher, as both would result in higher utility bills.

Table 3 presents the results of this analysis. I explore separately the effects of natural gas and electricity, which are the two most common fuels used for heating in the United States (in 2009, both were used by approximately 35% of households.) There is substantive variation on the type of fuel used across counties, with some counties almost completely electrified, and others using exclusively natural gas. As described in section 4, I exploit these differences to construct an instrument for exposure to changes in fuel price. I do so by interacting the baseline share of households which use each type of fuel (measured in 2009) in each county, by the average annual growth of the fuel price in the US.[24] The logic behind this approach is that counties in which households use more natural gas (electricity) for heating, are more vulnerable to changes in natural gas (electricity) prices.

Starting with natural gas, the first two columns of table 3 reveal that the coefficient of the triple interaction between HDD, natural gas share, and natural gas price growth is positive and significant for both filings and evictions. These results mean that the effect of HDD on filings and evictions *increases* in counties that use natural gas when national prices of this fuel increase. In the case of electricity, however, I find that the triple interaction between HDD, electricity share, and electricity price growth is not significantly different from zero for both filings and evictions. I postulate this could be due to the low variation in electricity prices during the period 2010-2016. Indeed, the standard deviation of growth rates of electricity prices during the period is 1.7 percentage points, whereas it is 9 percentage points for natural gas (approximately 5 times higher.) Hence, the low variation of price shocks during the period might be behind the lack of effect detected.

Finally, I explore which observable variables are correlated to the shares of households using both natural gas and electrification. As discussed in section 4, this exploration would increase confidence that the results presented above can be interpreted causally. The correlation matrix is presented graphically in figure 5. This figure shows that counties which use more natural gas tend to experience colder winters, have higher median incomes and fewer households living below the poverty rate, and are slightly more White. Counties that are more likely to use electricity as heating have a strong negative correlation to HDD. The strong correlation between electrification and warmer climate has been documented in the literature before (Davis, 2021). These counties are also poorer, and less White. Based on these correlates and the heterogeneous results presented in section 6 above, I would expect counties using mostly natural gas (which are colder, richer, and more White) to experience

[24] To compute a metric of annual price growth that is relevant for the winter season in which I am measuring HDD, I estimate growth during the winter of year y and the 9 months preceding with respect to the previous 12-month period.

a *weaker* relationship between HDD and eviction growth. This result provides confidence on the fact that the positive growth in evictions when natural gas prices increase in these counties does not operate through other observed channels.

Climate-sensitive industries I explore whether cold winter shocks might affect evictions through a labor channel. Cold winters might affect labor demand in industries more exposed to weather. This in turn could tighten the budget of workers in these industries, which are then less able to pay for rent.

To investigate this channel, I evaluate how the effect of HDD on evictions changes on counties with a larger share of workers in climate-sensitive industries. I consider an industry to be climate-sensitive if it is classified as a goods-producing industry by the Bureau of Labor Statistics. These industries—with a NAICS supersector code equal to 06—are natural resources and mining, construction, and manufacturing. These industries have been identified in the literature as more climate-sensitive (Addoum et al., 2019; Behrer and Park, 2017; Cai et al., 2018; Graff Zivin and Neidell, 2014).

I first divide the counties in the main sample into three terciles, according to the average share of the labor force working in a goods-producing industry during the winter months of 2005 to 2008 (so before the study period in this paper.) I run the main model in equation 1 into each of these terciles. Results from this analysis are summarized in the first three columns of table 4. It shows that the effect of HDD on filings and evictions is not different from zero in the two bottom terciles. However, 100 winter HDD increase both filings and evictions by 9% in counties with the largest share of goods-producing workers (both results are significant at the 1% level).

However, these results are just correlational. It could be that counties in the top tercile share other characteristics that are causing the observed effect. Figure 5 provides some support against this, as it shows that the share of goods-producing labor in a county is not strongly correlated with any of the observable variables associated with higher eviction growth (poverty rate, income, property values, percentage White, baseline winter HDD, etc.)

Nonetheless, other variables not accounted for could be leading the observed result. Hence, to gain further confidence on this channel, I exploit a similar shift-share instrument to the one used above for fuel prices. The logic behind this approach is that shocks to national average wages in goods-producing industries should affect counties more exposed, that is, with a higher share of workers in those industries. Then, I interact the HDD variable in the main model (equation 1) with the average growth rate of wages during the winter months in goods-producing industries in the United States.

Results are summarized in the last three columns of table 4. As expected under the hypothesis of a labor mechanism, higher aggregate wage growth *reduces* evictions and filings in counties with a higher share of workers in these industries. Its effect is not significant in other counties (evidenced by the interaction term not being significantly different from zero.) These results provide support for winter HDD impacting evictions through a labor channel.

However, given the precision of the estimates, I cannot rule out that the coefficients of both the main effects and interaction terms in the three terciles are equal.[25] The fact that industries classified as goods-producing by NAICS may have different levels of climate sensitivity might be adding some noise to the estimation.

Baseline health Finally, I explore whether HDD might affect evictions and filings through a health channel. The fact that cold weather worsens certain types of pathologies—notably respiratory and cardiovascular diseases—has been well documented in the epidemiology literature (Mercer, 2003; Analitis et al., 2008; Hassi, 2005; Gasparrini et al., 2015). Hence, it could be that cold winter shocks negatively impact health, which in turn decreases labor supply, rendering the affected population less able to afford rent.

To investigate this hypothesis, I explore how the effect of HDD on eviction filings changes across counties with different baseline mortality rates due to circulatory or respiratory diseases. Specifically, I run the main model (equation 1) on three terciles of the data separately, where counties are assigned to each tercile according to the average mortality share attributed to diseases of the circulatory or respiratory systems during the period 2005-2009 (Centers for Disease Control and Prevention, 2020). Results are in table 5. They show that, consistently with a health channel, the effects of HDD on filings are concentrated on counties with higher shares of mortality due to circulatory and respiratory diseases, while it is not different from zero on the bottom tercile.

Some caveats to this result are that, given the precision of the estimates, I cannot rule out that the coefficients for the three terciles are actually equal. Moreover, the measured differences are correlational, it could be that another variable associated with baseline health is causing the observed result. Figure 5 shows that counties with higher mortality due to cardiovascular and respiratory diseases are indeed poorer (with lower median incomes, and higher poverty rates), although they also tend to be Whiter. Even if results presented in table 5 seem to point out towards cold temperatures impacting evictions through a health channel, more research—ideally exploiting an exogenous health shock—is needed to assess the robustness of this mechanism.

[25] Hence, I cannot rule out that the triple interaction term between HDD, share of goods-producing industries, and wage growth in a model as in equation 3 is equal to zero.

8 Preventive policies: tenant-friendly regulation and disconnection rules

This section presents an exploratory analysis of whether two types of existing policies – state tenant-landlord regulations and rules that ban utilities disconnection – are effective in preventing the positive effect of cold weather shocks on evictions. I show that pro-tenant state regulations are correlated with a negligible impact of cold weather on evictions. However, pro-tenant disconnection rules are correlated with a stronger effect of cold weather on evictions.

State Landlord-Tenant Laws I first explore whether pro-tenant regulation at the state level is correlated with changes in the impact of HDD on evictions. To do so, I take advantage of a policy scorecard constructed by legal analysts at RentCafe (Brasuell, 2018). This scorecard ranks states based on how pro-tenant their landlord-tenant state laws are, exploring aspects such a deadlines for returning security deposits, rent-increase notices, etc. As it pertains to evictions, this scorecard also considers the procedure for handling lease termination notices (for non-payment, for lease violations, etc.) The scores assigned to each state are summarized in table A.4.

To assess the accuracy of this scorecard, I compare it with another developed by a different team of researchers, in a different period and context. Benfer et al. (2020b) develop a metric to quantify the extent to which states protect tenants from evictions during the COVID-19 pandemic. I use this score as a proxy of how pro-tenant a state legislature is. Both scorecards are positively correlated. Moreover, the results presented below are qualitatively similar using one scorecard or the other (results using metrics from Benfer et al. (2020b) not shown). This increases confidence that the scores used in the analysis appropriately reflect whether a state legislation leans pro-tenant or pro-landlord.

To perform the analysis, I use the policy scorecard to categorize states into two sets, pro-tenant (with policy scores above the median) and pro-landlord (with scores below the median.) I then run the main model in equation 1 (without controls) in each sample separately. Results are shown in table 6. I cannot rule out that the impact of HDD on filings and evictions is equal to zero (with a threshold significance level of 10%) in pro-tenant states. On the other hand, in pro-landlord states, the impact of HDD on evictions and filings is positive and significant.[26]

These results suggest that pro-tenant legislation is correlated with a lower effect of HDD on evictions. Figure 5 shows that pro-tenant states also tend to be colder, and with slightly higher incomes and a higher percentage of White residents. Thus, stronger pro-tenant reg-

[26]Testing the null hypothesis that the coefficients for pro-tenant and pro-landlord states are actually equal yields a p-value equal to 0.056 for evictions, and 0.366 for filings.

ulations could be another reason behind the lack of effect of HDD on evictions detected in counties with these characteristics in section 6. I cannot rule out, however, that this result is due to reverse causality. That is, states where evictions are less commonplace are more likely to pass pro-tenant legislation.

Ban on utilities disconnection Then, I evaluate how the impact of HDD on evictions changes with regulation that bans utility companies from disconnecting non-paying households during the coldest months of the year, or if temperatures fall below a certain threshold. Policies banning disconnection can alleviate the pressure on households on the verge of eviction, as these households might be able to default on utility bills without immediate repercussions. Table A.4 summarizes which states have date-based and/or temperature-based disconnection policies, with data coming from the U.S. Department of Health and Human Services (2018). Figure 5 shows that states with date-based disconnection policies have colder winters, and are less likely to use electricity for heating. Otherwise, date- and temperature-based disconnection policies are not strongly correlated with any of the other observables considered.

Table 7 shows the results of running the main model in equation 1 separately for counties with and without disconnection policies, with eviction filings as a dependent variable. These results show that, contrary to an argument that disconnection bans help curb evictions rates, HDD *increase* filings in counties with either temperature- or date-based disconnection policies (both coefficients are significant at the 1% level.) On the other hand, the effect of HDD on evictions is not significantly different from zero in counties without disconnection policies. Testing the null hypothesis that the HDD coefficients for states with and without disconnection rules are actually equal yields a p-value of 0.06 for date-based policies, and to 0.11 for temperature-based policies.

This seemingly counterintuitive result could have several explanations. It could be due to reverse causality. That is, states which experience large rates of utility disconnections and evictions can be more likely to react implementing pro-tenant legislation, such as policies banning utilities disconnection. However, these results would also be consistent with existing evidence that banning utility disconnections does not reduce evictions nor disconnections, it merely postpones them (Cicala, 2021; Desmond, 2016).

9 Conclusions

This paper provides evidence of a channel through which environmental shocks (colder winters) increase economic inequality. 100 more HDD during winter (approximately half of the standard deviation within counties) increase eviction filings by 3% and evictions by 2%

on average in the United States. Effects are driven by counties that are less White and have lower incomes. This paper provides evidence consistent with two main mechanisms operating the relationship between cold winters and evictions. The first is energy prices: higher heating fuel prices increase the effect of HDD on evictions. The second is a labor channel: the effect of HDD on evictions is concentrated on counties with larger shares of workers in industries more exposed to weather. A positive wage shock in those industries reduce the impact of cold winters. Given that households that face eviction experience lower future earnings and credit access (Collinson et al., 2021), evictions can deepen poverty and make it harder for households to escape situations of hardship. This paper illustrates that addressing energy poverty—for instance, through lower fuel taxes during the winter season—or providing larger benefits for workers of weather-exposed industries during cold winters might be effective approaches to reduce eviction rates.

Finally, a narrow interpretation of the main finding in this paper might lead to conclude that climate change could ameliorate the effect of temperatures on evictions, given that global average temperatures are increasingly raising. This interpretation can be challenged on three grounds. First, I find that even relatively small weather shocks lead to an increase in eviction and filing rates. The period of study, between 2010 and 2016, has had some of warmest years on historical record (NOAA, 2021). However, just half a standard deviation of winter HDD during that period has had sizable effects on filings and evictions. Second, given the two operating channels identified in this paper, relatively smaller cold weather shocks might still increase evictions if climate change also leads to higher energy prices (USGCRP, 2018) or disruptions in labor in climate-sensitive industries (Graff Zivin and Neidell, 2014). Finally, an active area of climate research posits that climate change, through the warming of the Arctic, might lead to *more* colder winter spells in the United States (Cohen et al., 2018), even as average annual temperatures increase. Hence, global average warming does not necessarily mean that the effects presented on this paper would dissipate.

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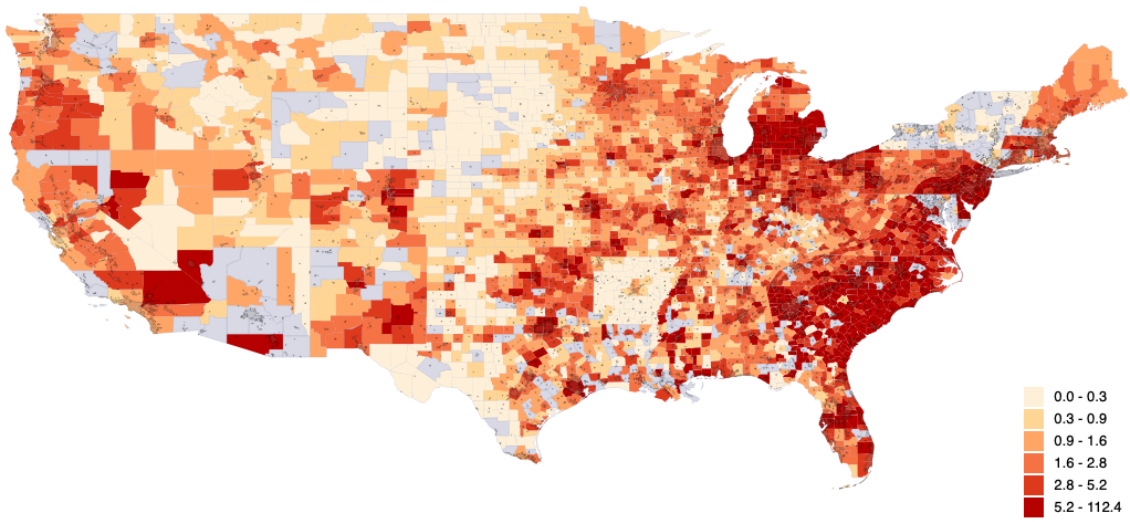
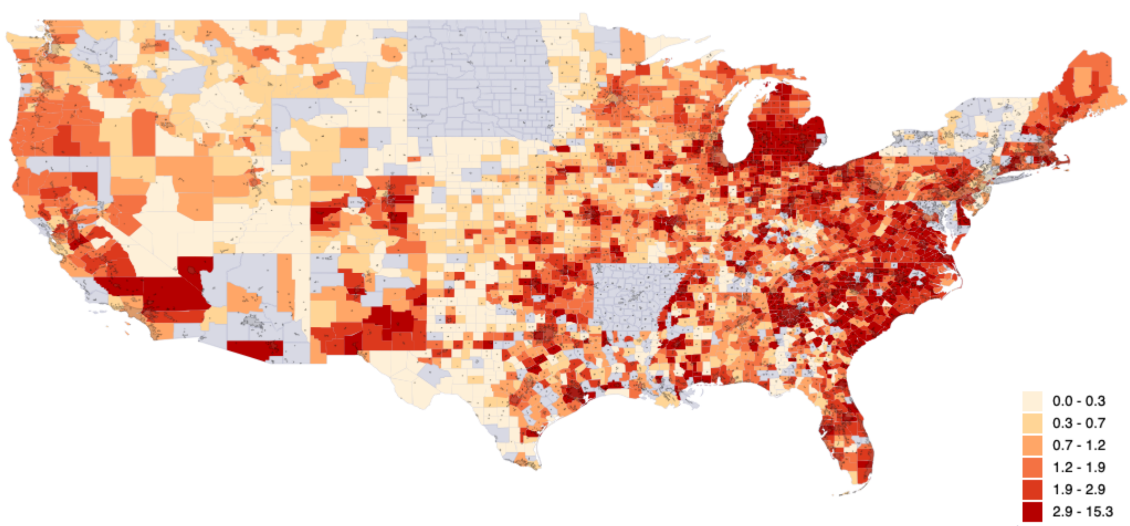


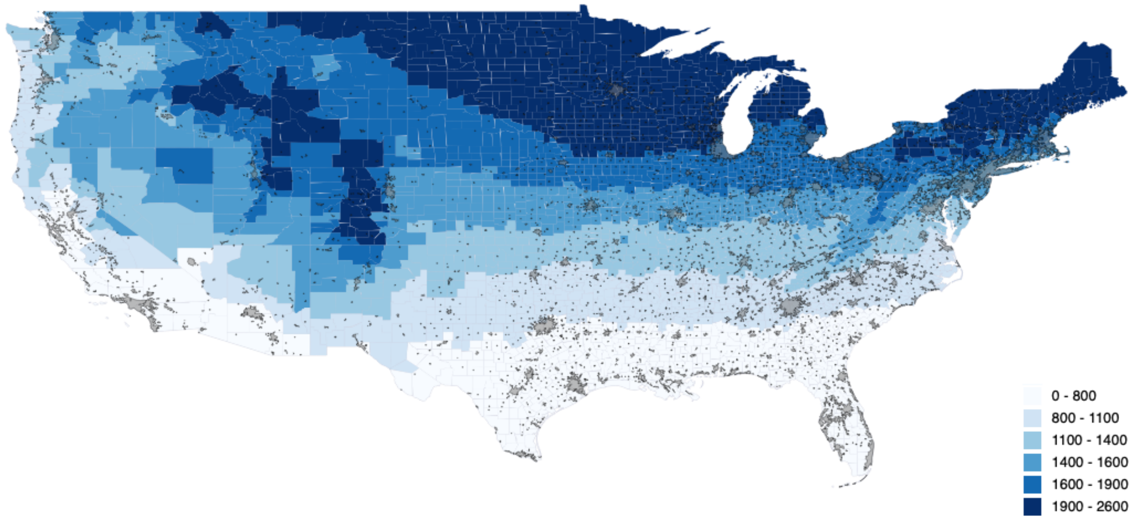
(a) Filings



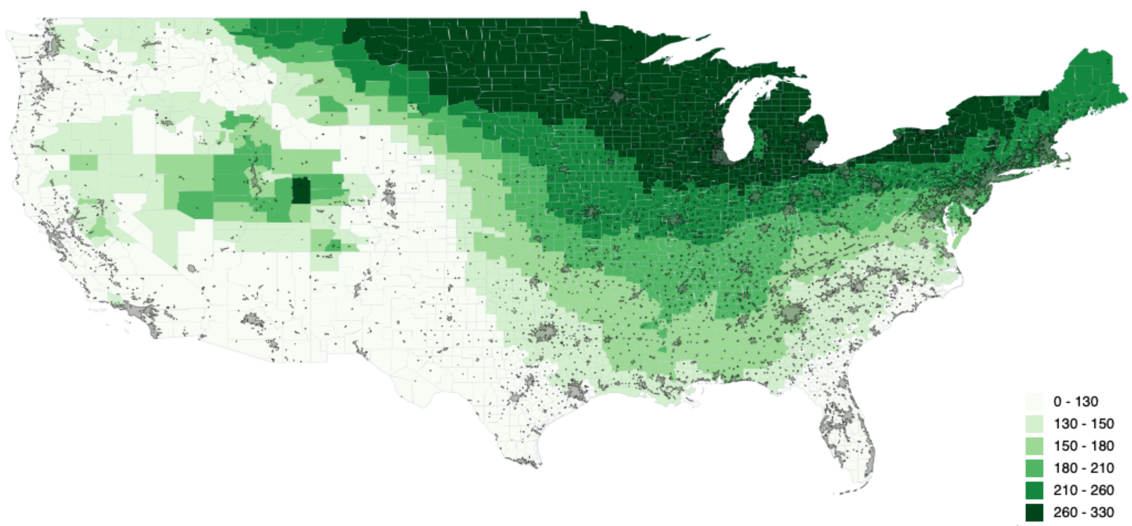
(b) Evictions

Figure 1: Average annual rate of filings and evictions

Notes: Figure shows the average rate of eviction filings (top) and evictions (bottom) during the study period. Counties shaded in gray do not have data on the relevant variable at any year during the study period. As described in section 3, data availability varies by county. Despite the comprehensiveness of the dataset, there is no data on evictions available for the states of Arkansas, North Dakota, and South Dakota. Urban areas are shaded in darker gray.



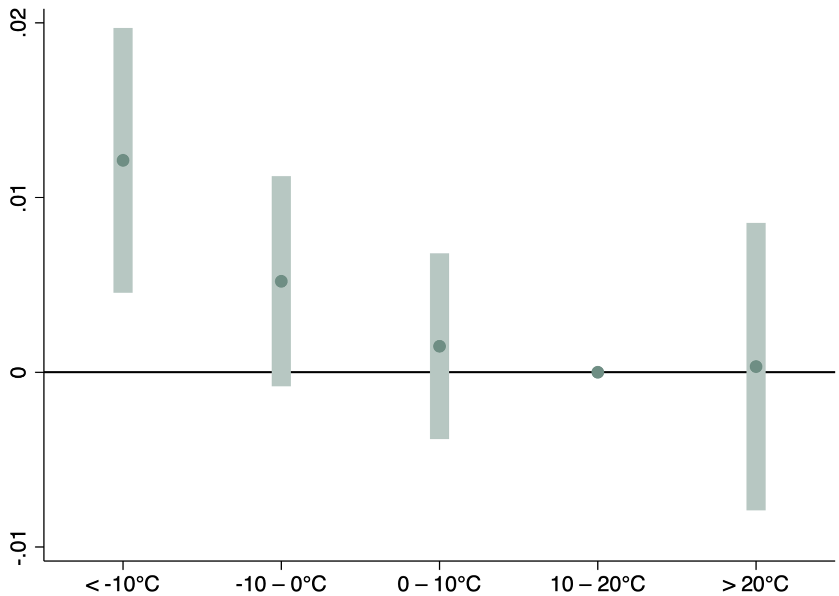
(a) Average



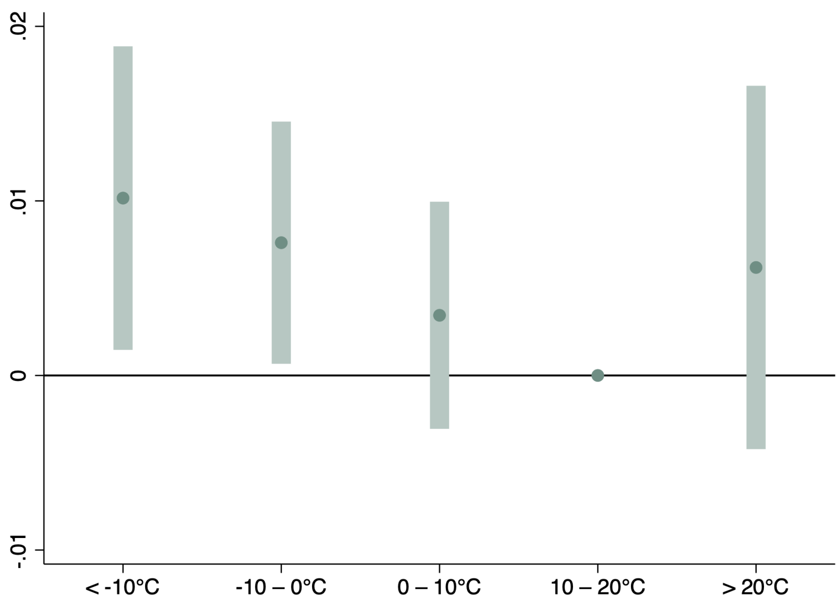
(b) Standard Deviation

Figure 2: Heating Degree Days in winter: average and standard deviation

Notes: Figure shows the average (top) and standard deviation (bottom) of the number of Heating Degree Days (HDD) during the months of January, February, and March during the study period (2010-2016). As described in section 3, HDD were computed with respect to a baseline temperature of 18°C (65°F), and account for partial days below the threshold temperature. Urban areas are shaded in gray.



(a) Filings



(b) Evictions

Figure 3: Impact of winter temperatures on filings and evictions: temperature bins

Notes: Figure shows the point estimates and 95% confidence intervals of the coefficients of the temperature-bin variables in the model described in equation 2. These variables denote the total time (in days) a particular county spent in each temperature interval during the winter months. The dependent variable is eviction filings (top) and evictions (bottom). The regression model also controlled for the one-year lag of the dependent variable (either filings or evictions), a quadratic polynomial in precipitation, and county and state-year fixed effects. Robust standard errors are clustered at the county level.

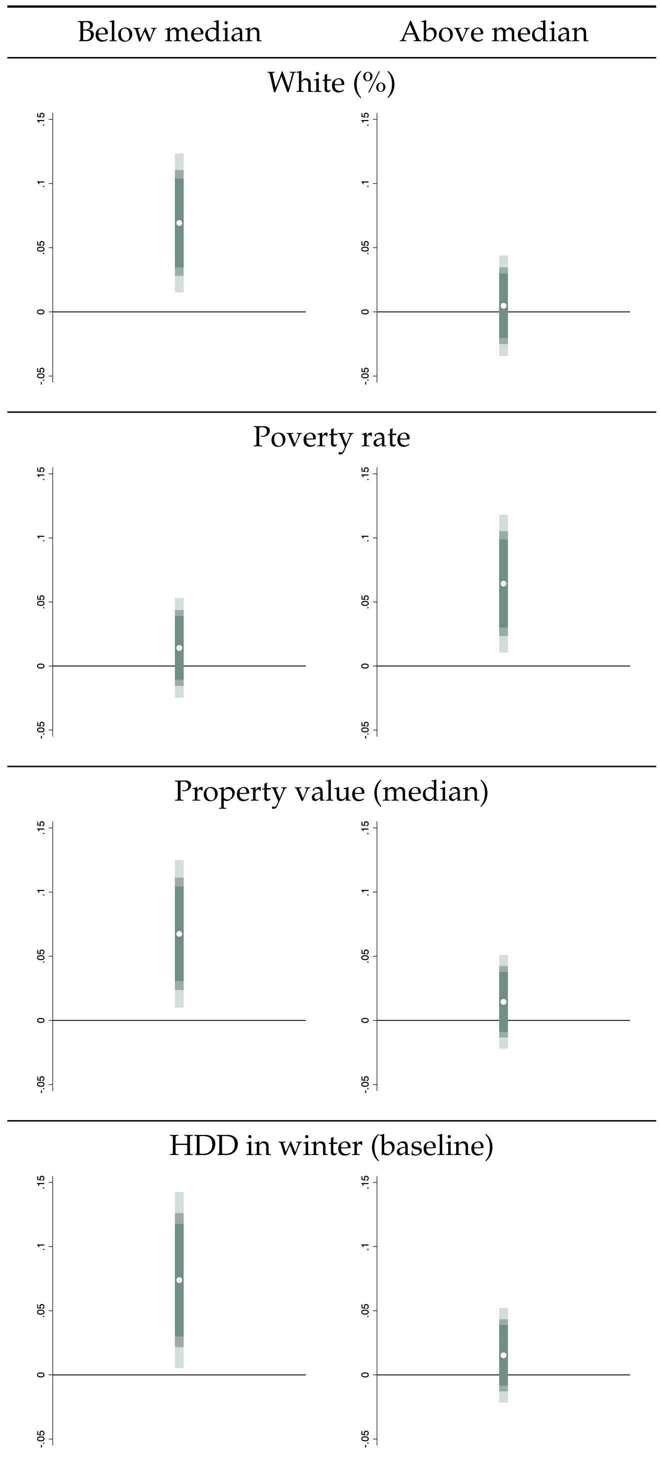


Figure 4: Heterogeneity in the relationship between HDD and eviction filings

Notes: This figure shows the point estimate and confidence intervals (90%, 95%, 99%, from darker to lighter shading) of the variable Heating Degree Days in winter after running the main estimation model (equation 1) with filings as a dependent variable on different subsets of the data. Data subsets are defined as counties above or below the sample median of (from top to bottom): percentage of White population, poverty rate in county, median property value, and average number of heating degree days in winter during the period 2000-2005. All variables are measured before the starting year of the study period (2010) so they are not possibly affected by future HDD.

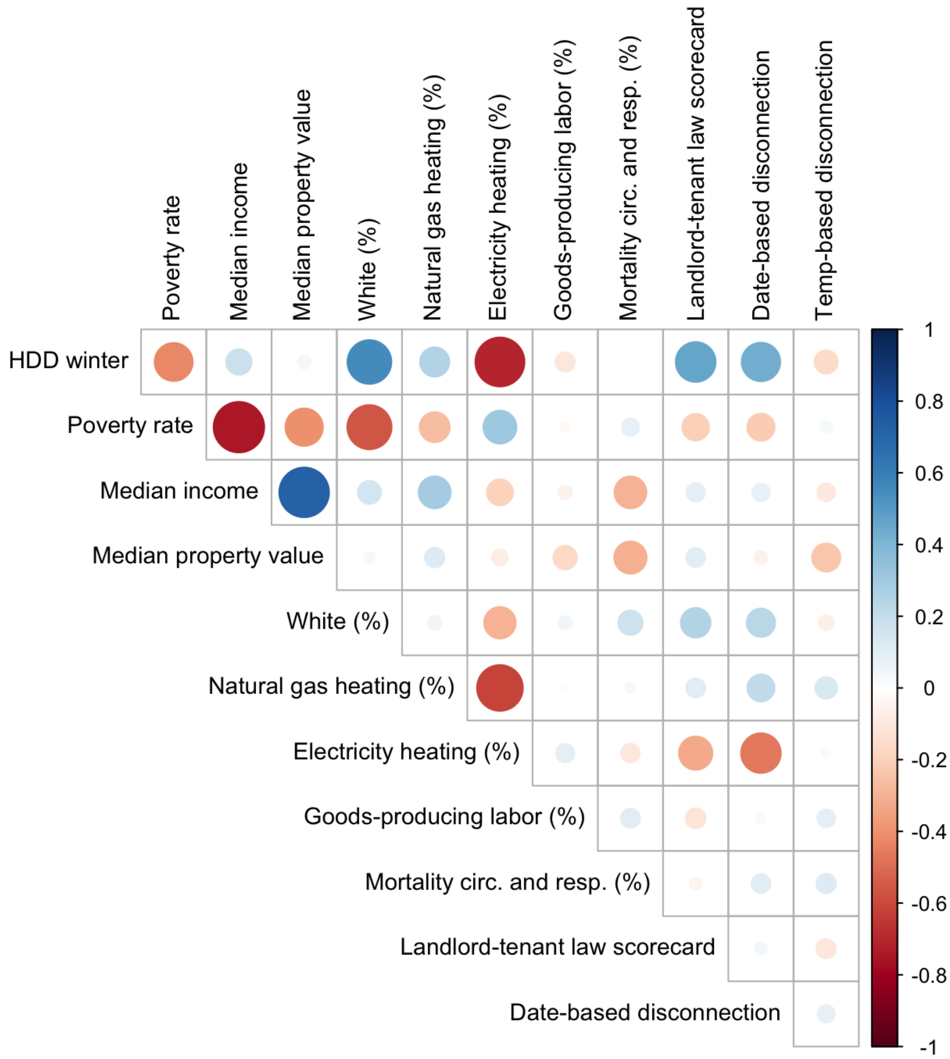


Figure 5: Correlation between county characteristics at baseline

Notes: Figure shows all pairwise Pearson correlation coefficients among the baseline levels of the main independent variable (winter Heating Degree Days) and baseline values of variables along which heterogenous effects are measured.

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Variable	Mean	SD (within)	SD (between)	N	Counties	Years (average)
HDD winter	1382	183	512	21728	3104	7.0
Filings	885	457	4415	18813	2827	6.7
Evictions	375	279	1445	17525	2643	6.6

Table 1: Summary Statistics

Notes: Summary statistics of the explanatory variable in main model (*HDD, winter*: Heating Degree Days during the first quarter of the year) and main dependent variables (*Filings* and *Evictions*, number of annual eviction filings and evictions by county, respectively.)

	Panel A: Evictions Filings (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
HDD winter$_{c,y}$	0.033***	0.033***	0.036***	0.031**	0.038***	0.044***
	(0.012)	(0.012)	(0.011)	(0.013)	(0.011)	(0.012)
Filings (log)$_{c,y-1}$			0.19***	0.19***	0.19***	0.19***
			(0.016)	(0.016)	(0.016)	(0.016)
HDD fall$_{c,y-1}$				0.0093		
				(0.020)		
HDD spring$_{c,y}$				0.030		
				(0.030)		
HDD winter$_{c,y-1}$					0.026**	0.027**
					(0.012)	(0.012)
HDD winter$_{c,y-2}$						0.036***
						(0.012)
Precipitation (cuadratic)	×	✓	✓	✓	✓	✓
P-value joint H_0				0.009	0.002	0.000
Observations	16,313	16,313	15,348	15,348	15,348	15,348

	Panel B: Evictions (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
HDD winter$_{c,y}$	0.021	0.021	0.021*	0.025*	0.022*	0.031**
	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)
Evictions (log)$_{c,y-1}$			0.20***	0.20***	0.20***	0.20***
			(0.017)	(0.017)	(0.017)	(0.017)
HDD fall$_{c,y-1}$				-0.029		
				(0.022)		
HDD spring$_{c,y}$				0.022		
				(0.031)		
HDD winter$_{c,y-1}$					0.011	0.013
					(0.014)	(0.014)
HDD winter$_{c,y-2}$						0.048***
						(0.014)
Precipitation (cuadratic)	×	✓	✓	✓	✓	✓
P-value joint H_0				0.167	0.207	0.002
Observations	15,130	15,130	14,213	14,213	14,213	14,213

Table 2: Main Results: Impacts of Cold Winters on Evictions Filings and Evictions

Notes: Table shows the main result of the paper: cold weather shocks during winter increase the rate of households who are served an eviction order and are finally evicted. Dependent variable is log of eviction filings in county *c* in year *y* (top panel), and the log of evictions (bottom panel.) *HDD* measures 100 heating degree days during the winter months of year *y* over county *c*. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. *P-value joint* H_0 row summarizes the p-value of testing the null hypothesis that all coefficients of the HDD variables are jointly equal to zero. Significance levels: * p< 0.1, ** p< 0.05, *** p< 0.01.

	Natural Gas		Electricity	
	(1)	(2)	(3)	(4)
	Filings	Evictions	Filings	Evictions
HDD winter$_{cy}$	0.052***	0.035**	0.032**	0.030*
	(0.013)	(0.015)	(0.016)	(0.017)
HDD winter$_{cy}$ $\times$NG share$_c$ $\times$NG price growth$_y$	0.17***	0.14**		
	(0.059)	(0.069)		
HDD winter$_{cy}$ $\times$Elec share$_c$ $\times$Elec price growth$_y$			-0.18	-0.30
			(0.34)	(0.46)
Observations	16,313	15,130	16,313	15,130

Table 3: Mechanisms: Fuel Prices

Notes: Table shows heterogeneity in the impacts of heating degree days on filings and evictions according to changes in heating fuel prices. Dependent variable is log of eviction filings—columns (1) and (3)—or the log of evictions—columns (2) and (4)—in county c in year y. *HDD* measures 100 heating degree days during the winter months of year y over county c. *NG (Elec) share* is the share of households which use natural gas (electricity) for heating in county c at baseline. *NG (Elec) price growth* is the growth of natural gas (electricity) national average price during the winter of year y and the 9 months preceding with respect to the previous 12-month period. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Evictions Filings (log)						
	(1)	(2)	(3)	(4)	(5)	(6)
HDD winter$_{cy}$	0.016	-0.012	0.090***	0.0090	-0.0026	0.10***
	(0.020)	(0.021)	(0.024)	(0.021)	(0.023)	(0.026)
HDD winter$_{cy}$ $\times$Wage growth$_{y}$				0.17	-0.25	-0.30*
				(0.18)	(0.17)	(0.18)
Tercile	1	2	3	1	2	3
Observations	4,983	5,518	5,750	4,983	5,518	5,750

Panel B: Evictions (log)						
	(1)	(2)	(3)	(4)	(5)	(6)
HDD winter$_{cy}$	0.0092	-0.030	0.086***	-0.0016	-0.018	0.12***
	(0.022)	(0.023)	(0.029)	(0.023)	(0.024)	(0.032)
HDD winter$_{cy}$ $\times$Wage growth$_{y}$				0.27	-0.34*	-0.78***
				(0.20)	(0.18)	(0.23)
Tercile	1	2	3	1	2	3
Observations	4,575	5,154	5,343	4,575	5,154	5,343

Table 4: Mechanisms: Climate-sensitive industries

Notes: Table shows heterogeneity in the impacts of heating degree days on filings (top panel) and evictions (bottom panel) according to the share of labor force in climate-sensitive industries in county c at baseline. Each model is run in one tercile of the data—noted on the row *Tercile*. Counties are assigned to a tercile according to the share of the total labor force working in climate-sensitive industries during the months of January, February, and March at baseline. Climate-sensitive industries are defined as goods-producing industries (NAICS super-sector 06) and include: natural resources and mining, construction, and manufacturing. Dependent variable is log of eviction filings in county c in year y (top panel), and the log of evictions (bottom panel.) *HDD* measures 100 heating degree days during the winter months of year y over county c. *Wage growth* measures the average growth in wages during the first quarter of year y in goods-producing industries in the United States. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)
HDD winter$_{cy}$	0.026	0.054**	0.056**
	(0.020)	(0.022)	(0.023)
Tercile	1	2	3
Observations	5,299	5,465	5,370

Table 5: Mechanisms: Mortality due to diseases of the circulatory or respiratory systems

Notes: Table shows heterogeneity in the impacts of heating degree days on filings according to the share of mortality related to diseases of the circulatory or respiratory systems in county c at baseline. Dependent variable is log of eviction filings in county c in year y. *HDD* measures 100 heating degree days during the winter months of year y over county c. Each model is run in one tercile of the data—noted on the row *Tercile*—according to the share of the total mortality due to diseases of the circulatory or respiratory systems in county c at baseline. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Filings		Evictions	
	(1)	(2)	(3)	(4)
HDD $\text{winter}_{\text{cy}}$	0.045**	0.023	0.050**	-0.0037
	(0.019)	(0.016)	(0.022)	(0.018)
State landlord-tenant laws	Pro-landlord	Pro-tenant	Pro-landlord	Pro-tenant
Observations	8,318	7,995	7,620	7,510

Table 6: Heterogeneity according to State Landlord-Tenant Laws

Notes: Table shows heterogeneity in the impacts of heating degree days on filings and evictions according to whether existing landlord-tenant regulations at the state level lean pro-tenant or pro-landlord. Dependent variable is log of eviction filings—columns (1) and (2)—or log of evictions—columns (3) and (4)—in county c in year y. *HDD* measures 100 heating degree days during the winter months of year y over county c. Each model is run in a subset of the data—noted on the row *State landlord-tenant laws*—according to whether existing landlord-tenant regulations lean pro-tenant or pro-landlord. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
HDD winter$_{cy}$	0.046***	-0.0081	0.052***	0.014
	(0.014)	(0.026)	(0.018)	(0.016)
Date-based disconnection	✓	×	–	–
Temperature-based disconnection	–	–	✓	×
Observations	10,829	5,484	8,050	8,263

Table 7: Heterogeneity according to State Disconnection Laws

Notes: Table shows heterogeneity in the impacts of heating degree days on filings and evictions according to whether utility disconnection is banned based on date- and temperature-based criteria. Dependent variable is log of eviction filings in county c in year y. *HDD* measures 100 heating degree days during the winter months of year y over county c. Each model is run in a subset of the data, according to whether utility disconnection is banned in certain dates—row *Date-based disconnection*—or if temperatures fall below a certain temperature—*Temperature-based disconnection*. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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Appendices

Appendix A Additional tables

	(1)	(2)	(3)	(4)	(5)	(6)
HDD winter$_{c,y}$	0.026**	0.043***	0.036***	0.036*	0.036***	0.036*
	(0.011)	(0.014)	(0.011)	(0.018)	(0.011)	(0.015)
HDD area	Urban	All	All	All	All	All
Sample	Main	No issues	Balanced	Main	Main	Main
Cluster SE	County	County	County	State	County×Year	County Year
Observations	12,974	9,886	15,348	15,348	15,348	15,348

Table A.1: Robustness: Impacts of Cold Winters on Filings

Notes: Table summarizes the robustness checks performed on the main result, that include: measuring HDD only over urban areas (column 1); limiting the sample to observations where filings were recorded without issues (column 2); limiting the sample to counties with filings data in every year throughout the study period (column 3); or different levels of clusterization of standard errors (columns 4, 5, and 6.) Dependent variable in all models is the log of eviction filings in county c in year y. *HDD* measures 100 heating degree days during the winter months of year y over county c. All models include one year lag of filings, a quadratic in precipitation, and county and state-year fixed effects. Robust standard errors are clustered at the county level. Significance levels: * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$.

	Temporal lag (years)		
Cutoff (km)	1	2	5
100	0.012	0.012	0.012
500	0.015	0.015	0.015
1000	0.015	0.015	0.016
2000	0.015	0.015	0.016

Table A.2: Main effects spatially and serially correlated standard errors

Notes: Table shows the resulting standard errors of the HDD variable the in main model (equation 1) after allowing for both spatial and serial correlation (up to the *Cutoff* and *Temporal lag* indicated, respectively), as in Conley (1999) with code developed in Hsiang (2010).

	Filings		Evictions	
	(1)	(2)	(3)	(4)
CDD $\text{summer}_{c,y}$	-0.025	-0.0048	-0.010	-0.0026
	(0.025)	(0.025)	(0.029)	(0.029)
CDD $\text{fall}_{c,y}$		-0.17***		-0.12*
		(0.060)		(0.073)
CDD $\text{winter}_{c,y}$		0.099		0.12
		(0.069)		(0.086)
CDD $\text{spring}_{c,y}$		-0.035		-0.0043
		(0.035)		(0.037)
P-value joint H_0		0.055		0.464
Observations	16,313	16,313	15,130	15,130

Table A.3: Impacts of Hot Summers on Filings and Evictions

Notes: Table measures the effects of hot summers on evictions and filings. Dependent variable is the log of eviction filings—columns (1) and (2)—and the log of evictions—columns (3) and (4)—in county c in year y. *CDD* measures 100 cooling degree days (computed with a reference temperature of 18°C, approximately 65°F) over county c during the relevant season of year y. All models include county and state-year fixed effects. Robust standard errors are clustered at the county level. *P-value joint* H_0 row summarizes the p-value of testing the null hypothesis that all coefficients of the CDD variables are jointly equal to zero. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

State	Landlord-Tenant Scorecard	Date-based Disc. Ban	Temperature-based Disc. Ban
Alabama	37.5	×	✓
Arkansas	12.5	✓	✓
Arizona	70	×	✓
California	60	×	×
Colorado	32.5	×	×
Connecticut	42.5	✓	×
District of Columbia	70	×	✓
Delaware	80	✓	✓
Florida	35	×	×
Georgia	25	✓	✓
Iowa	55	✓	✓
Idaho	27.5	✓	×
Illinois	37.5	✓	✓
Indiana	35	✓	×
Kansas	65	✓	✓
Kentucky	55	×	×
Louisiana	25	×	×
Massachusetts	55	✓	×
Maryland	42.5	✓	×
Maine	67.5	✓	×
Michigan	50	✓	×
Minnesota	60	✓	✓
Missouri	42.5	✓	✓
Mississippi	30	✓	×
Montana	55	✓	✓
North Carolina	25	✓	×
North Dakota	52.5	×	×
Nebraska	62.5	✓	×
New Hampshire	60	✓	×
New Jersey	62.5	✓	✓
New Mexico	52.5	✓	×
Nevada	65	×	×
New York	37.5	✓	×
Ohio	30	✓	×
Oklahoma	52.5	✓	✓
Oregon	65	×	×
Pennsylvania	62.5	✓	×
Rhode Island	72.5	✓	✓
South Carolina	42.5	×	✓
South Dakota	65	✓	×
Tennessee	55	×	✓
Texas	37.5	×	✓
Utah	47.5	✓	×
Virginia	45	×	×
Vermont	90	✓	×
Washington	62.5	✓	×
Wisconsin	55	✓	✓
West Virginia	12.5	×	×
Wyoming	25	✓	✓

Table A.4: States Laws: Landlord-Tenant and Utilities Disconnection

Notes: Table summarizes the status of relevant state policies. The policy scorecard presented in column 1 categorizes state landlord-tenant regulations according to how supportive of tenants these regulations are, with 0 representing more pro-landlord regulations, and 100 more pro-tenant (Brasuell, 2018). The last two columns summarize whether a state has regulations that ban utility disconnection during certain dates (column 2), or if the temperature falls below a certain threshold (column 3).

Variable(s)	Data source
Evictions and eviction filings by county	Desmond et al. (2018b)
Heating Degree Days	Computed from gridded daily minimum and maximum temperatures provided by Schlenker (2020)
Baseline demographics (median income, %White, poverty rate, median property value)	Desmond et al. (2018b), who summarize these data from the 2000 Census and the American Community Survey 5-Year Data (2009)
Natural gas and electricity prices by year	U.S. Energy Information Administration (2021)
Share of heating fuel by county	American Community Survey 5-Year Data (2009). Table B25040. U.S. Census Bureau (2021)
Wages by industry and quarter of year	U.S. Bureau of Labor Statistics (2020)
Share of labor force in goods-producing industries (NAICS supersector 06)	U.S. Bureau of Economic Analysis (2020)
Share of total mortality due to cardiovascular and respiratory mortality	Centers for Disease Control and Prevention (2020)
Landlord-tenant policy scorecard	Scorecards developed by Benfer et al. (2020b) and legal analysts at RentCafe (Brasuell, 2018)
Utility disconnection policies by State	U.S. Department of Health and Human Services (2018)
Consumer Price Index - Urban	U.S. Bureau of Labor Statistics (2017)
Urban areas extent	U.S. Census Bureau (2012)

Table A.5: Data Sources

Notes: Table summarizes all data sets and sources used in this paper.