Flattening the Eviction Curve:
A Quasi-Experimental Evaluation of the Brooklyn Center Tenant Protection Ordinance

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Abstract

This paper uses two quasi-experimental methods—synthetic control (SC) and difference-in-differences (DiD)—to evaluate the effects of the 2022 Brooklyn Center Tenant Protection Ordinance. The ordinance was adopted at a time when eviction filings were on the rise across the state. Descriptive statistics provide an indication that after the ordinance was adopted, Brooklyn Center's eviction rate did not increase by as much as the eviction rate in other parts of suburban Hennepin County. For SC models, I compared Brooklyn Center to most other Hennepin County cities. I found statistically significant evidence that the ordinance reduced eviction rates in the period 37-48 weeks after policy adoption. This result survived several placebo tests (though it was sensitive to whether Brooklyn Park was included in the donor pool). Results for filing rates did not survive all placebo tests. For DiD, I drew from a sample of most block groups in suburban Hennepin County. Conditioning on pre-treatment covariates via doubly robust DiD, I found the policy brought reduced eviction rates and filing rates in some of the first eight months after policy adoption. DiD models survived a wide variety of robustness checks. SC and DiD provided consistent evidence of reduced eviction rates in some periods of time. The two methods produced mixed evidence on filing rates, and did not produce strong evidence of policy effects for other outcomes. This paper concludes that when evictions spiked across Minnesota following the expiration of COVID-19 eviction moratorium policies, the City of Brooklyn Center flattened the eviction curve.

Keywords: Eviction, Displacement, Eviction Moratorium, COVID-19, Just Cause, Pre-Eviction Notice, Housing, Landlord-Tenant, Tenant Protections, Policy, Local Policy, Public Policy, Brooklyn Center, Hennepin County, Effectiveness, Causal, Causal Inference, Evaluation, Impact Evaluation, Program Evaluation, Quasi-Experimental, Difference-in-Differences, Event Study, Synthetic Control

Executive Summary

In the early phase of the COVID-19 pandemic, U.S. policymakers adopted expansive protections for tenants. Among these, federal and state eviction moratoria banned most evictions. Most of Minnesota's COVID-era tenant protections expired by the fall of 2021. Around the same time, eviction filings began to increase sharply across the state.

In this context, the City of Brooklyn Center adopted a Tenant Protection Ordinance on February 28, 2022. Brooklyn Center is a northern suburb of Minneapolis. The ordinance included two major provisions: (a) protections against lease nonrenewal without just cause, and (b) a 30-day pre-eviction notice requirement. Then-Mayor Mike Elliott said he believed the ordinance would promote "stability in housing" (Miller, 2022). In *The White House Blueprint for a Renters Bill of Rights*, the Biden Administration endorsed policies similar to those contained in Brooklyn Center's ordinance. The administration contended that just cause requirements may "prevent evictions," and advocated for "30 days' notice" before evictions (Domestic Policy Council & National Economic Council, 2023, p. 16).

If policies like Brooklyn Center's ordinance prevent evictions, that would carry important implications for tenants and communities overall. Past research has shown that evictions cause substantial negative consequences, including increased hospital use and decreased earnings (Collinson et al., 2023). Policies preventing eviction likely bring large benefits for the people who would otherwise experience displacement and homelessness, as well as indirect benefits for taxpayers (who contribute to the cost of emergency room care).

In this paper, I present suggestive evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods of time after its adoption in early 2022. With limited prior literature on whether just cause and pre-eviction notice policies affect eviction rates, this paper contributes new insights on how local government policies may change the likelihood of displacement, homelessness, and associated perverse outcomes. I used two statistical methods to estimate causal effects: synthetic control and difference-in-differences.

In synthetic control models, I essentially compared the trend of eviction rates in Brooklyn Center to a weighted average of the trend in similar Hennepin County cities. By comparing trends before and after policy adoption, synthetic control allows researchers to check whether policies changed outcomes. I used data on evictions going back to 2015 for cities in suburban Hennepin County. The main synthetic control model suggests the Brooklyn Center Tenant Protection Ordinance reduced the rate of evictions in some periods. Before policy adoption the eviction rate trend was about the same for Brooklyn Center and the comparison cities, and after policy adoption Brooklyn Center's eviction rate trend did not rise as sharply as the comparison trend. While synthetic control models for eviction rates survived several placebo tests, the result was sensitive to whether Brooklyn Park was included in the donor pool.

The second causal inference method, difference-in-differences, yielded similar results. In difference-in-differences models, I compared eviction rates by month in Brooklyn Center and other parts of suburban Hennepin County. I aggregated data at the level of the Census block group, and applied control variables to weight the comparison group so it would approximately match Brooklyn Center in terms of characteristics like education levels, household income, and race and ethnicity. DiD shows that in some periods after policy adoption, Brooklyn Center had a lower monthly eviction rate than the comparison group. The estimated average treatment effect on the treated for period 3 (the fourth 30-day period after policy adoption) is -13.340. The corresponding *p*-value is 0.011. In this period, there is

statistically significant evidence that the ordinance reduced Brooklyn Center's eviction rate by about 13 monthly evictions per 10,000 renter-occupied housing units. The DiD model survived a wide variety of robustness checks (and results were about the same in a specification where the sample was restricted to exclude Brooklyn Park). DiD results suggest the ordinance reduced eviction rates, at least in some periods of time.

Triangulating across methods, when discussing policy-relevant conclusions I focus on findings for eviction rates. Both synthetic control and difference-in-differences provided statistically significant evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some of the periods of time after the policy was adopted in early 2022. While not definitive, these two causal inference methods provide suggestive evidence consistent with a causal interpretation of the policy's effects on eviction rates. That is, I contend that the most plausible interpretation of the effects of Brooklyn Center's ordinance is that it reduced the extent to which evictions increased in Brooklyn Center in some periods following the expiration of state and federal eviction moratorium policies. Synthetic control and difference-in-differences suggest that at least in some periods of time, evictions would have increased by even more in Brooklyn Center if the city had not adopted its Tenant Protection Ordinance.

I suggest two main directions for future research. First, future research could focus on the racial justice implications of tenant protection policies. In this paper I present some exploratory analysis of whether there were disparate policy effects by race and ethnicity. I partitioned the sample, focusing separately on places with more renters of color and with more white non-Hispanic renters. To the extent Brooklyn Center's ordinance prevented evictions, it appears the policy was most effective in neighborhoods with more renters of color. This analysis is consistent with the possibility that the ordinance made it more difficult for landlords to discriminate against renters of color, but the methods used in this paper did not allow for direct analysis of discrimination. Future work could provide additional evidence on whether policies like the Brooklyn Center ordinance changed the likelihood of discriminatory practices by landlords.

Second, future research could build on this analysis and evaluate the extent to which tenant protection policies like Brooklyn Center's ordinance prevent displacement. A future study could incorporate a wider sample of cities and a longer time period. It may be possible to apply contemporary approaches to difference-in-differences, and check for both short- and long-term effects on eviction rates that can be attributed to the adoption of tenant protection policies. To facilitate future research in this area, state or local governments could implement policies to track the issuance of pre-eviction notices. While I had access to court records of eviction cases, this analysis could have been stronger with a direct measure of how often landlords sent notice that they were planning to initiate an eviction action. Publicly accessible data on the issuance of pre-eviction notices could make it easier to quantify how often tenants and landlords resolve disputes before reaching the courthouse.

This paper has several policy implications. As this is among the first studies to evaluate the effects of local just cause and pre-eviction notice policies, I contribute new suggestive evidence that such policies may reduce the rate of evictions (at least in some periods and in places like Brooklyn Center). More broadly, this paper presents evidence consistent with the claim that local governments can reduce displacement by regulating the landlord-tenant relationship. After the expiration of Minnesota's eviction moratorium, filings spiked statewide. In this context, it appears that the City of Brooklyn Center flattened the eviction curve.

Table of Contents

Introduction

This paper presents a two-pronged quasi-experimental evaluation of the Brooklyn Center Tenant Protection Ordinance. During the COVID-19 pandemic, the U.S. federal government and the Minnesota state government adopted temporary tenant protections. These policies included eviction moratoria, banning most eviction actions. After the expiration of these protections in late 2021, eviction filings increased sharply across Minnesota. In this context, the city of Brooklyn Center, Minnesota adopted its Tenant Protection Ordinance in early 2022. Brooklyn Center is a northern suburb of Minneapolis. The ordinance includes a 30-day pre-eviction notice requirement and a provision that landlords must have just cause if they choose not to renew a lease.

Analyzing the effects of the ordinance via two quasi-experimental methods, synthetic control (SC) and difference-in-differences (DiD), I conclude that there is suggestive evidence that the ordinance reduced eviction rates in some periods of time. Accounting for the limitations of the two causal inference methods used here, when discussing policy-relevant conclusions I focus on eviction rates since a wide variety of models tell a consistent story regarding policy effects on eviction rates. Results for other measures, like eviction filing rates, were less consistent across specifications. Results for eviction rates survived a variety of robustness checks. For example, the main DiD result survived a check where I aggregated data across space in a different way. At the end of this paper, I discuss overall interpretations and suggest future directions for quantitative and qualitative research. Altogether, I suggest that the most plausible interpretation of the effects of the Brooklyn Center Tenant Protection Ordinance is that it reduced the rate of evictions (at least in some periods after policy adoption). In other words, Brooklyn Center flattened the eviction curve.

Background: Evictions, COVID-19, and policy

A large body of research has established negative effects associated with evictions. Drawing from Chicago and New York administrative records of eviction cases, Collinson et al. (2023) used instrumental variables to estimate causal effects of evictions on a variety of outcomes. The authors found that evictions caused decreased earnings, and increased homelessness and hospital use (Collinson et al., 2023, pp. 1, 45, 48, 55). Another recent study assessed the short- and long-term relationship between evictions and health outcomes for young adults. The authors showed that evictions were associated with worse health status, and that health status remained lower seven years later (Hatch & Yun, 2021, pp. 469, 478, 487). Through an ethnographic study focused on tenant experiences in Milwaukee, Desmond (2016) explored some of the pernicious effects of evictions: “[f]amilies lose not only their home, school, and neighborhood, but also their possessions: furniture, clothes, books” (Desmond, 2016, p. 296). Evictions are harmful for tenants, leading to displacement and homelessness as well as pernicious outcomes in terms of economic security and health.

There are important disparities surrounding the negative effects of evictions and homelessness. One study showed that eviction filings and judgments were most heavily concentrated among Black tenants (Hepburn et al., 2020, p. 649). Gender was an important part of the story: Black and Latinx women experienced evictions more often than Black and Latinx men (Hepburn et al., 2020, p. 649). Like with evictions, homelessness is disproportionately common among people of color: people who are Black, Hispanic, Pacific Islanders, or Native American are all disproportionately likely to be homeless (Evans et al., 2019, p. 63). The population without stable housing also disproportionately includes veterans, people who have experienced domestic violence, people who have experienced major mental health problems, and people who have received an HIV diagnosis (Evans et al., 2019, p. 63). Evictions are

harmful, and the people who get evicted tend to be among the most disadvantaged members of local communities.

In early 2020, perhaps in recognition of the possibility that COVID-19 would bring unique challenges to those experiencing housing insecurity, the U.S. federal government took steps to limit the risk of eviction. Under the CARES Act of March 2020, the federal government implemented an initial moratorium on eviction filings through late July of that year (McCarty & Carpenter, 2020, p. 1; Centers for Disease Control and Prevention, 2021). The CARES Act moratorium applied to properties that receive federal support such as Low Income Housing Tax Credits or Housing Choice Vouchers (McCarty & Carpenter, 2020, p. 2). Separately, starting in early September 2020, the Centers for Disease Control and Prevention (CDC) implemented its own national eviction moratorium (Hurley & Wolfe, 2021; Nande et al., 2021; Centers for Disease Control and Prevention, 2021). After extending the moratorium several times, the CDC contended that there was a "likelihood of mass evictions nationwide" if the moratorium were to expire (Centers for Disease Control and Prevention, 2021). On August 26, 2021, the Supreme Court put an end to the CDC eviction moratorium (Hurley & Wolfe, 2021; Nande et al., 2021).

In Minnesota, eviction filings plummeted amid COVID-19 moratoria. Filings dropped sharply in 2020, and remained low in 2021. Amid the continuing health crisis and changing federal policies, in 2021 Minnesota lawmakers implemented a statewide eviction moratorium with a phased offramp (Davis & Matsumoto, 2021). There was also a temporary statewide pre-eviction notice policy (Volunteer Lawyers Network, 2021). Most protections expired by the fall of 2021: starting October 12, Minnesota landlords were permitted to file evictions against all tenants except those with pending applications for rent help (Davis & Matsumoto, 2021). As of June 1, 2022, all protections expired (Davis & Matsumoto, 2021). After a temporary drop in 2020 and 2021, Minnesota eviction filings rose to high levels in 2022. These patterns are apparent in **Table 1** below: in Hennepin County and Minnesota as a whole, evictions fell sharply in 2020, remained low during the two years with temporary federal and state tenant protection policies, and then rose sharply in 2022 after the expiration of most protections.

Table 1. Eviction filings by year in Hennepin County & statewide, 2018-2022.

	2018	2019	2020	2021	2022
Hennepin County	5,540	5,640	1,649	1,478	7,214
Minnesota	17,293	17,934	5,653	5,829	22,734

Note: Data drawn from MN Judicial Branch District Court Data. Statewide figures include filings for Hennepin County (Minnesota Judicial Branch, n.d.).

Some researchers have evaluated the effects of COVID-era eviction policies. Hepburn et al. (2023) found that eviction moratoria led to large reductions in eviction filing rates (Hepburn et al., 2023, p. 186). An and Tzur-Ilan (2022) found that during eviction moratoria evictions decreased, households spent more on groceries, and households were less likely to experience food insecurity (An et al., 2022, pp. 1–4) Ali and Wehby (2022) showed that state eviction moratoria improved the mental health status of renters (Ali & Wehby, 2022, p. 1583). This body of research indicates that eviction moratoria seem to have helped renters weather the pandemic.

During COVID-19, three Hennepin County cities enacted local policies that included pre-eviction notice requirements: Minneapolis, St. Louis Park, and Brooklyn Center (City of St. Louis Park, 2020; City

of Minneapolis, 2021; City of Brooklyn Center, 2022a, 2022b; HOME Line, 2022).[1] Pre-eviction notice policies require landlords to inform tenants that they are planning to initiate an eviction prior to formally filing an eviction action with the court. Tenants have an opportunity to address concerns during the intervening period. For example, if a landlord alleges that a tenant has not paid their rent, the notice period might provide a tenant with a chance to provide proof of payment or to seek assistance. Of the three Hennepin County cities that enacted local pre-eviction notice provisions, just Brooklyn Center adopted its policy at a time when evictions were taking place at substantial levels (Agenda: City Council Meeting, 2022, p. 103). I focus my analysis on Brooklyn Center due to the timing of this city's ordinance. With measurable eviction trends before and after the adoption of the ordinance, and data for Brooklyn Center and surrounding areas, there is an opportunity to use trends over time to evaluate policy effects.

Brooklyn Center adopted its Tenant Protection Ordinance on February 28, 2022 (City of Brooklyn Center, 2022b). The policy included two key provisions: a 30-day pre-eviction notice requirement, and a provision banning the non-renewal of leases without "just cause." ACER, a community organization based in the northern suburbs of Minneapolis, advocated for an ordinance that would give tenants more time to prepare to contest eviction filings (Agenda: City Council Meeting, 2022, p. 3).[2] For cases of alleged non-payment or material breach of lease, Brooklyn Center's ordinance requires landlords to provide tenants with 30 days' notice prior to filing an eviction (City of Brooklyn Center, 2022a; HOME Line, 2022). Tenants have the opportunity to take corrective action and thereby avoid the court process, such as by paying past due rent (City of Brooklyn Center, 2022b, pp. 2–3). During City Council discussions, there was a debate about whether the policy should include a 14- or 30-day notice requirement; the 30-day provision won out (Agenda: City Council Meeting, 2022, pp. 7–11). Regarding just cause, the ordinance permits landlords to choose not to renew a lease only if they can cite a valid reason such as nonpayment of rent, breach of lease, or a plan to renovate the property (City of Brooklyn Center, 2022b, p. 4). The ordinance only applies to the subset of rental properties in the city (those that are deemed affordable to households at 80% of area median income) (HOME Line Legal Staff, 2022). In practice, the Tenant Protection Ordinance covers nearly all rental housing units in Brooklyn Center, as rent prices in this city tend to be low enough to be governed by the policy (HOME Line Legal Staff, 2022). So, after the ordinance went into effect in early April 2022, Brooklyn Center provided that most renters would receive 30 days' notice before a landlord could initiate an eviction action, and limited the circumstances when landlords could elect not to renew leases.

This paper's contribution: studying the effects of a local ordinance on evictions

In this paper, I seek to evaluate the effects of the Brooklyn Center Tenant Protection Ordinance. I focus on two main research questions:

1. Did the 2022 Brooklyn Center Tenant Protection Ordinance reduce the rate of evictions?

2. Did the 2022 Brooklyn Center Tenant Protection Ordinance reduce the rate of eviction filings?

One recent research project, the 2022 *Brooklyn Center Housing Report*, provides context for these questions. The research team, led by Dr. Brittany Lewis, described landlord and tenant

[1] During the 2023 legislative session, Minnesota adopted a statewide 14-day pre-eviction notice requirement. The policy went into effect on January 1, 2024. This paper does not include analysis of the state pre-eviction notice policy. All data used in this paper comes from earlier periods.

[2] Disclosure: I consulted with ACER as part of my research process.

experiences with housing in Brooklyn Center. Among survey respondents, the authors found that housing prices were among the most common reasons residents chose to move to Brooklyn Center (Lewis et al., 2022, p. 9). Despite the relatively low housing prices in this city compared to other parts of the Twin Cities region, Lewis et al. reported that over half of Brooklyn Center renters are cost-burdened, with about 20% of renters paying the majority of their income for housing (Lewis et al., 2022, p. 2). The authors also provided important context on the city's demographics: Brooklyn Center has the highest Black population share in the Minneapolis-St. Paul metropolitan area, and is one of two cities in the region with a majority non-white population (along with Brooklyn Park) (Lewis et al., 2022, p. 2).

This paper complements the Lewis et al. study by implementing quasi-experimental methods to study local eviction dynamics. There is still a need for additional research on evictions in Brooklyn Center. Lewis et al. reported that "[o]ne notable absence in conversations with both renters and landlords [was] the subject of evictions," noting that this was "surprising given Brooklyn Center's elevated eviction rate relative to Hennepin County as a whole" (Lewis et al., 2022, p. 8). Further, this paper provides new context on housing in Brooklyn Center by applying quantitative methods. Lewis et al. primarily used qualitative methods; the authors stated that "a rigorous statistical analysis" fell outside their report's scope (Lewis et al., 2022, p. 8). In this paper, by using quasi-experimental methods to analyze Brooklyn Center eviction patterns, I contribute a new body of evidence on housing policy in this Minneapolis suburb.

This paper contributes new evidence on the effects of just cause policies (when paired with pre-eviction notice). I have not come across much prior research on how just cause policies affect eviction rates. One flawed 2019 paper used difference-in-differences to analyze the effects of just cause protections in four California cities (Cuellar, 2019). The topline result was that just cause policies reduced eviction rates by 0.808 percentage points. There were some important problems with the Cuellar study that call its results into question, and this paper extends beyond that prior work. First and most important, Cuellar used post-treatment covariates to select comparison cities. While the four treated cities adopted just cause policies between 2002 and 2010, the author used covariates from 2000-2016 when constructing propensity scores to identify comparison cities. This approach was problematic, as it allowed the effects of the ordinance to shape the selection of the comparison group. Unlike Cuellar's study, this paper only applies pre-treatment covariates. Second, my analysis of Brooklyn Center evictions has a more systematic approach to account for demographic differences between local areas. The DiD models in this paper are doubly robust, following the approach of Sant'Anna and Zhao to allow for inference "even if either (but not both) the propensity score model or the outcome regression models are misspecified" (Sant'Anna & Zhao, 2020, p. 105). By contrast, the Cuellar (2019) approach to DiD was not doubly robust, and the propensity scores used to select comparison cities did not account for race and ethnicity. Among other pre-treatment covariates, my approach to doubly robust DiD controlled for block group-level data on the shares of householders who were white non-Hispanic and Hispanic of any race. A third area of comparative strength of this paper is that it uses DiD event studies instead of two-way fixed effects (TWFE). In the past few years, a body of literature has identified numerous problems with TWFE.[3] One relevant problem is that TWFE cannot account for causal effects that vary over time. Last, I triangulate between two causal inference techniques, rather than relying on just one method. Altogether, compared to Cuellar (2019) this paper provides a more plausible account of the effects of local ordinances that include just cause protections.

[3] More details are provided in the section describing my approach to difference-in-differences.

This paper contributes to the literature on the effectiveness of local tenant protection policies. Hatch (2017) reported that "scholars and policymakers know very little about…what effect particular laws or legal tendencies have on renter outcomes" (Hatch, 2017, p. 114). Some researchers have described the relationship between state landlord-tenant policy and eviction rates. Merritt and Farnworth (2021) used block group-level data to show that states with policies that favor tenants had lower eviction rates and eviction filing rates (Merritt & Farnworth, 2021, p. 562). The authors characterized Minnesota as a "protectionist" state, with policies that tend to favor tenants (Merritt & Farnworth, 2021, p. 566). Raymond et al. (2021) analyzed block group-level data to estimate whether events like hurricanes had effects that varied based on state landlord-tenant policy (Raymond et al., 2022, pp. 36, 46–47). They showed that eviction rates increased by the most in states with policies that favored landlords (Raymond et al., 2022, pp. 46–47). Like Merritt and Farnworth (2021) and Raymond et al. (2021), in this analysis of Brooklyn Center evictions I focus on block group-level data while analyzing policies that were implemented at a higher level. By focusing on a specific local landlord-tenant policy, I provide greater specificity than do researchers who have focused on broad categories for state-level landlord-tenant policy. Raymond et al. stated that one "important avenue" for future research would be to assess "whether individual statutes reduce evictions" (Raymond et al., 2022, p. 48). By analyzing the effects of an individual local policy on eviction rates, this paper contributes to the literature on how policy choices affect outcomes for renters.

Applying synthetic control and difference-in-differences to evaluate the effects of the Brooklyn Center Tenant Protection Ordinance, this paper provides new insights suggesting that city policies that incorporate pre-eviction notice and just cause requirements may prevent evictions (at least in some periods of time). This paper also reports exploratory analysis suggesting that benefits were concentrated in the parts of Brooklyn Center with more renters of color. These findings may be useful to policymakers seeking to reduce the displacement of local residents, or to reduce housing disparities by race and ethnicity.

Empirical Strategy

In this section, I provide an overview of my empirical strategy for evaluating the effects of the Brooklyn Center Tenant Protection Ordinance on eviction rates and eviction filing rates. I used two methods: difference-in-differences (DiD) and synthetic control (SC). From a systematic literature review, I identified DiD as one promising approach to evaluate the effects of local landlord-tenant policies like the Brooklyn Center ordinance. Details on the systematic literature review are provided in **Appendix A**. Considering other possible methods, I identified synthetic control as a viable alternative to DiD. The main advantage of SC and DiD is that these two methods allow researchers to compare trends across geography, and see whether trends changed after some event of interest that affected some places and not others. In this paper, I use SC and DiD to compare eviction rates in Brooklyn Center with rates in other parts of Hennepin County, before and after the adoption of the Brooklyn Center Tenant Protection Ordinance in early 2022.

Given the unique dynamics of COVID-19, my empirical strategy focuses on how best to isolate the effects of the Brooklyn Center ordinance. One concern is that jurisdictions other than Brooklyn Center could have adopted policies that changed eviction trends during the period of interest. I followed Goodman-Bacon and Marcus' recommendation that evaluations of COVID-19 policies should "focus on situations where treatment and control groups differ only by the introduction of a single COVID-19 policy (or, at least, only a few policies)" (Goodman-Bacon & Marcus, 2020, pp. 155–156). I restricted the sample to one local government context (Hennepin County), and removed the two cities that adopted

similar ordinances before Brooklyn Center (Minneapolis and St. Louis Park). All units in the treatment and comparison groups shared the same federal, state, and county government context, reducing concerns about the adoption of other policies related to COVID-19 (Goodman-Bacon & Marcus, 2020, pp. 155–156). In addition, the SC and DiD models used in this paper all involve procedures to "impose balance" on demographic characteristics before policy adoption, reducing concerns about treatment effects that could have affected some groups with more or less intensity (Goodman-Bacon & Marcus, 2020, p. 156).

Data

Both DiD and SC require longitudinal panel data, with repeated observations of the same units. To construct panels, I processed administrative data on eviction filings, geocoded filings against defendant households, and aggregated records by time period and geographic area. I obtained administrative records of Hennepin County eviction filings from the Community GIS program at the University of Minnesota's Center for Urban and Regional Affairs (CURA).[4] CURA, in turn, obtained these data from the Minnesota Judicial Branch. This dataset included all eviction cases filed from January 1, 2015 through June 23, 2023, in Minnesota's Fourth Judicial District (which covers Hennepin County). Expunged cases are presumably missing from the data. Initially, the dataset included 87,563 observations. Each observation was a party in a closed eviction case. For the same case, raw data included separate records for the landlord and the tenant. I removed observations for plaintiffs, to allow for a focus on the tenants against whom eviction actions were filed.

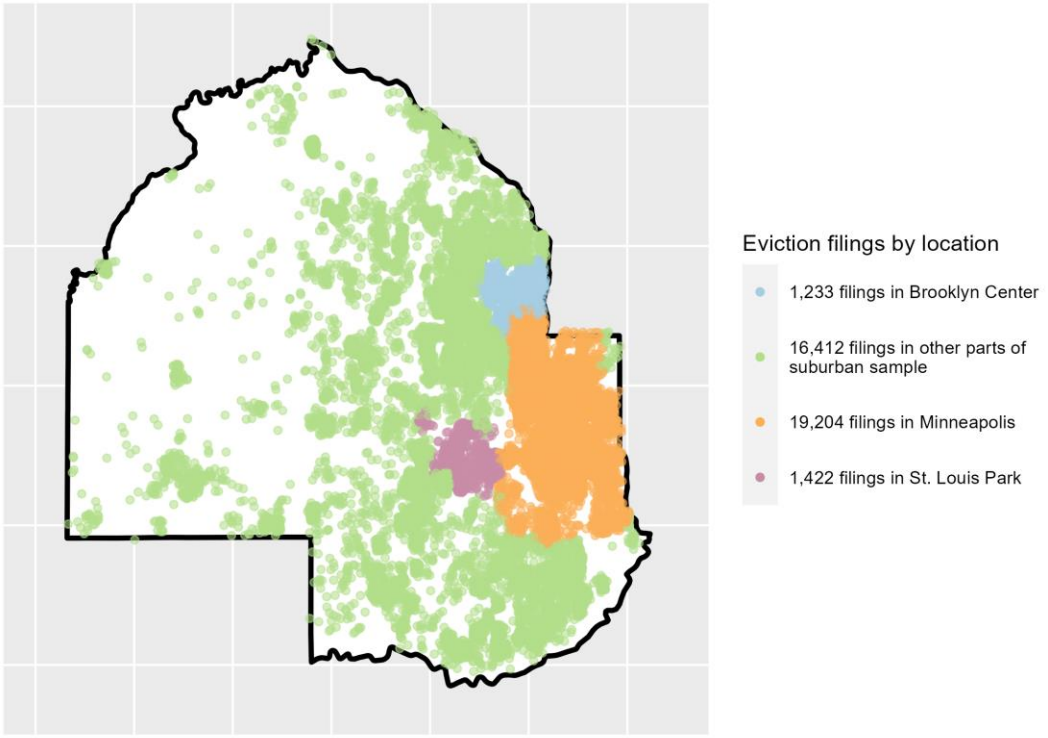
In this paper I analyze effects on both eviction rates and eviction filing rates. For evictions, I follow the approach of Collinson et al. (2023), defining evictions as "an eviction order that requires the tenant to vacate the property" (Collinson et al., 2023, p. 8). Some cases resulted in a judgment of eviction that would authorize the landlord to recover the rental housing unit (Office of Minnesota Attorney General Keith Ellison, n.d.). When I refer to evictions in my discussion of court data, I generally refer to closed eviction cases where the court-ordered judgment was recorded as an eviction. Focusing on this definition of evictions likely leads to an underestimate of displacement. This variable does not include settlements that resulted in displacement, and excludes informal evictions that took place outside the court system. Choosing to focus on eviction filings and judgments has a major advantage: it is possible to quantify these outcomes with available data. To allow for analysis of change over time, I used date variables provided by the court system. When analyzing eviction filing rates, I used the dates when eviction cases were filed. When analyzing eviction rates, I used the dates of eviction judgments.

Using defendant addresses, I identified the geographic coordinates of households involved in eviction cases. I used the Google Maps Platform API as well as the ggmaps package in R to geocode the addresses. I had a 99.3% hit rate, indicating that the geocoding process identified geographic coordinates for all but 299 of the 40,647 defendant addresses in the raw data. After geocoding, I restricted the sample to remove observations from Minneapolis and St. Louis Park, and to exclude observations with addresses outside Hennepin County. Data were more likely comprehensive within the county. 2,077 geocoded observations had addresses located outside Hennepin County, indicating that some defendant addresses were located outside Hennepin County for unknown reasons, or that there may have been errors in the geocoding process for some addresses. I removed these observations. I also restricted the sample to remove some duplicate records of eviction filings (explained below). The

[4] Disclosure: I have worked as a research assistant at CURA, including a role as part of the Community GIS program.

remaining cases are shown in **Fig. 1** below, with some random noise added to protect privacy.

Fig. 1. Defendant addresses in Hennepin County eviction filings, 1/1/2015 – 6/23/2023.

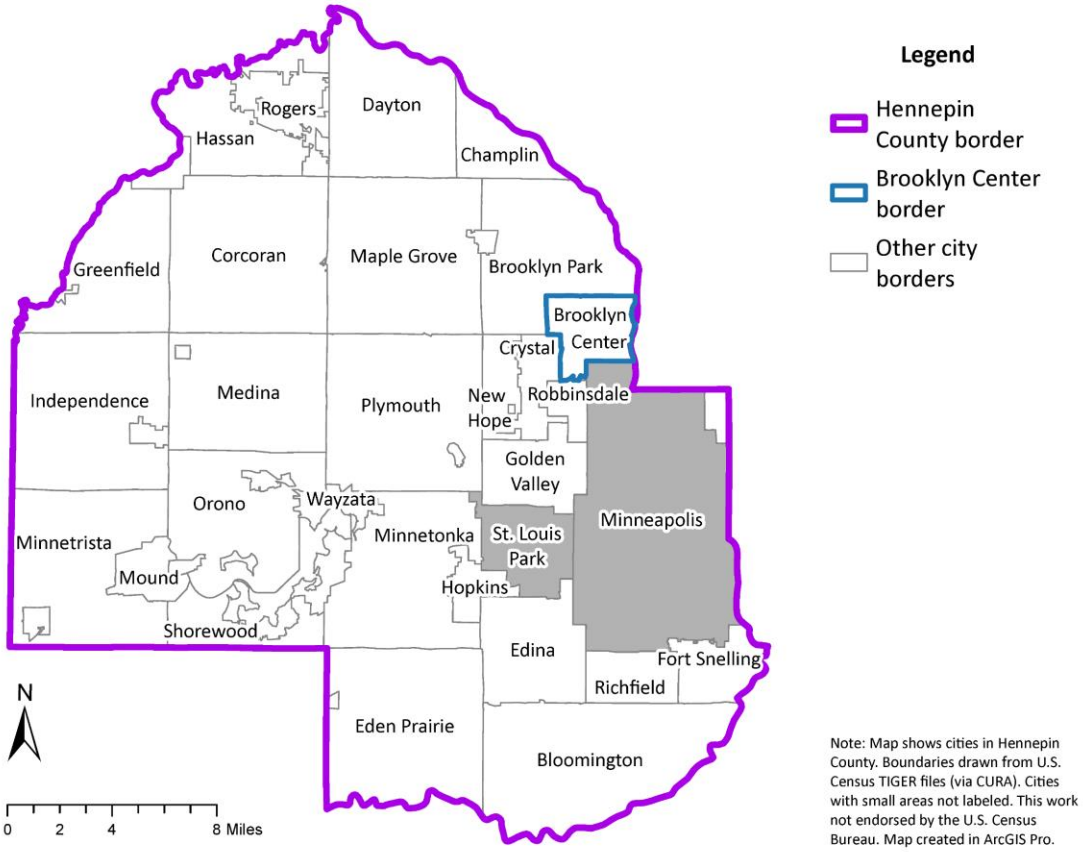


Note: Eviction filing data geocoded in R with ggmap and Google Maps API. In this plot, coordinates randomly vary by up to 0.5 miles from the true location (to protect privacy). Sample excludes filings with coordinates outside Hennepin County. Duplicate records of eviction filings on the same date with the same address removed, leaving the unit of analysis as eviction filings of a defendant household at an address on a day. Data: MN Judicial Branch via CURA; OpenStreetMap. Plotted in R with ggmap; ggplot2; geom_sf; st_jitter.

This research focuses on patterns of residential displacement; accordingly, it was important to ensure that the data reflected *residential* evictions as opposed to commercial evictions. After restricting the sample to suburban Hennepin County, I used two procedures to check whether a sizable fraction of defendants were commercial entities. First, I constructed a random sample of forty filings, and searched Minnesota Court Records Online to check whether there was an indication that any defendants were entities other than households (Minnesota Judicial Branch, 2023). I did not find any evidence to that effect. However, I did find that there were two observations with the same case number and filing date. I decided to remove duplicate filings with the same case number and filing date, to construct data where the unit of analysis could be understood as defendant households in eviction cases. Second, I filtered the data using a snippet of code designed to capture any commercial entities. My colleague Dr. Anthony Damiano has conducted extensive research on evictions in Hennepin County, and he generously shared a snippet of code he had used to remove commercial defendants from a similar dataset (Damiano, 2023). This code is designed to remove defendants if their names included words like “pizza” or abbreviations like “LLC” that would tend to indicate the defendant was a business instead of a person. Using a version of Dr. Damiano’s code did not identify any commercial entities in the suburban sample. After applying the two procedures described above, I concluded that it was reasonable to use the assumption that the data reflected only residential eviction cases.

I constructed panels using two different geographic levels: County subdivisions (basically, cities) and Census block groups. I used the Census Data API to link the geographic coordinates of each filing with the corresponding city in suburban Hennepin County. **Fig. 2** below shows cities in Hennepin County. Minneapolis and St. Louis Park are presented in gray, to reflect that these cities are excluded from the analysis in this paper. The other areas of the County are the suburban sample. Panels by city count up eviction actions by city in 12-week periods. Each city appears multiple times in the panel (once for each 12-week period). This allows for analysis of change over time in city-level eviction trends.

Fig. 2. Map of cities in the Hennepin County suburban sample.

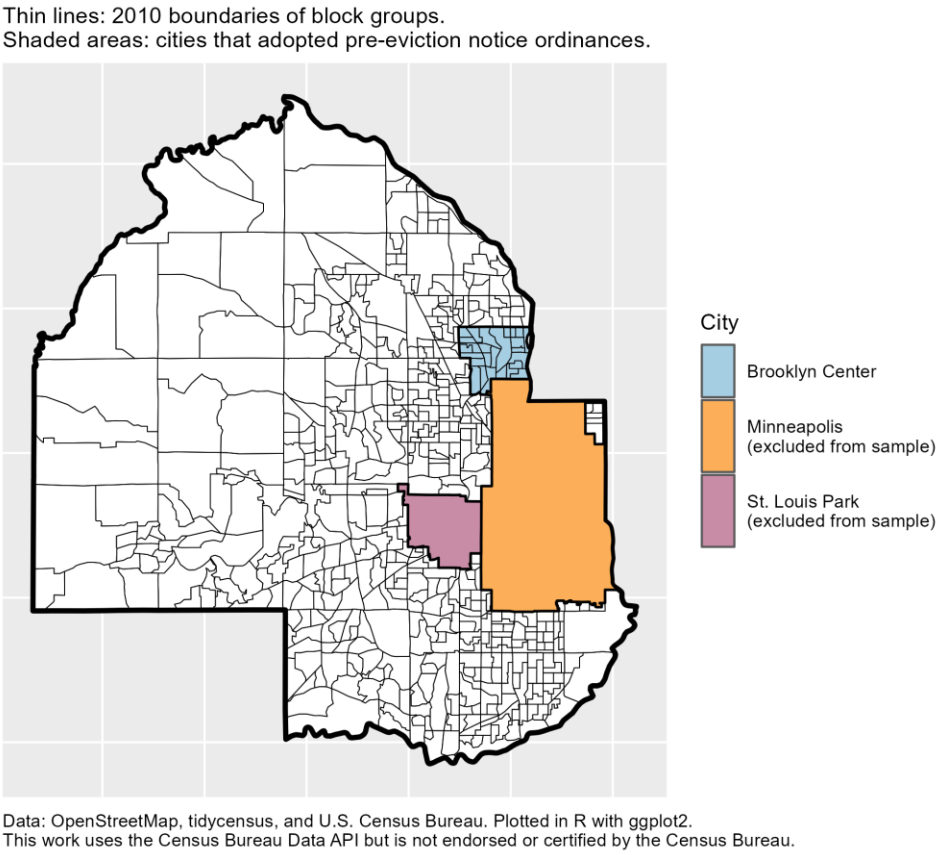


When aggregating data by Census block group, I chose to use the boundaries set in 2010. The Census Bureau assigns boundaries for Census tracts that span Hennepin County. In turn, tracts are divided into Census block groups. To reflect changes in neighborhood populations, every decade the Census Bureau changes the borders of the block groups. In this analysis, I had to make a choice about whether to use the 2010 or 2020 boundaries, as the bulk of the pre-COVID data available came from the 2015-19 period, and then the evictions of interest before and after the Brooklyn Center ordinance fell in late 2021 and 2022. In the middle of this timeframe, the borders of the block groups and tracts changed in the year 2020. Focusing on the 2010 block group boundaries had the advantage of allowing for comparison of Brooklyn Center neighborhoods to other parts of Hennepin County in terms of pre-COVID demographic characteristics. When applying covariates by Census geography, I primarily used American

Community Survey (ACS) data for the period 2015-19, drawing from IPUMS USA, IPUMS NHGIS, IPUMS GeoMarker, the U.S. Census Bureau, the Google Maps Platform Data API, and Social Explorer (Ruggles et al., 2023; Manson et al., 2022; U.S. Census Bureau, 2023; Google Maps Platform, 2023; Social Explorer & U.S. Census Bureau, 2023; Oakes et al., 2019).[5] I used the tidycensus R package to generate a variable indicating the block group under 2010 boundaries corresponding to each defendant address (Walker & Herman, 2023).

Fig. 3 below illustrates how I used geographic information to construct panels by block group. The thin black lines are the 2010 borders of Census block groups. The figure highlights Brooklyn Center (in blue) as well as the other cities that adopted pre-eviction notice policies. The suburban sample is the set of block groups that do not overlap with Minneapolis or St. Louis Park. These areas are shown in white and blue. Panels count up eviction actions by block group in 30-day periods. Each block group appears multiple times in these panels (once for each 30-day period). This approach allows for analysis of change over time from late 2021 to late 2022.

Fig. 3. Hennepin County block groups and selected city borders.



The approach of applying covariates at low levels of Census geography (like the block group) has been used in past regression analysis focused on local housing dynamics. In a study on evictions and

[5] While I draw from Census data, this research has not been reviewed or endorsed by the U.S. Census Bureau.

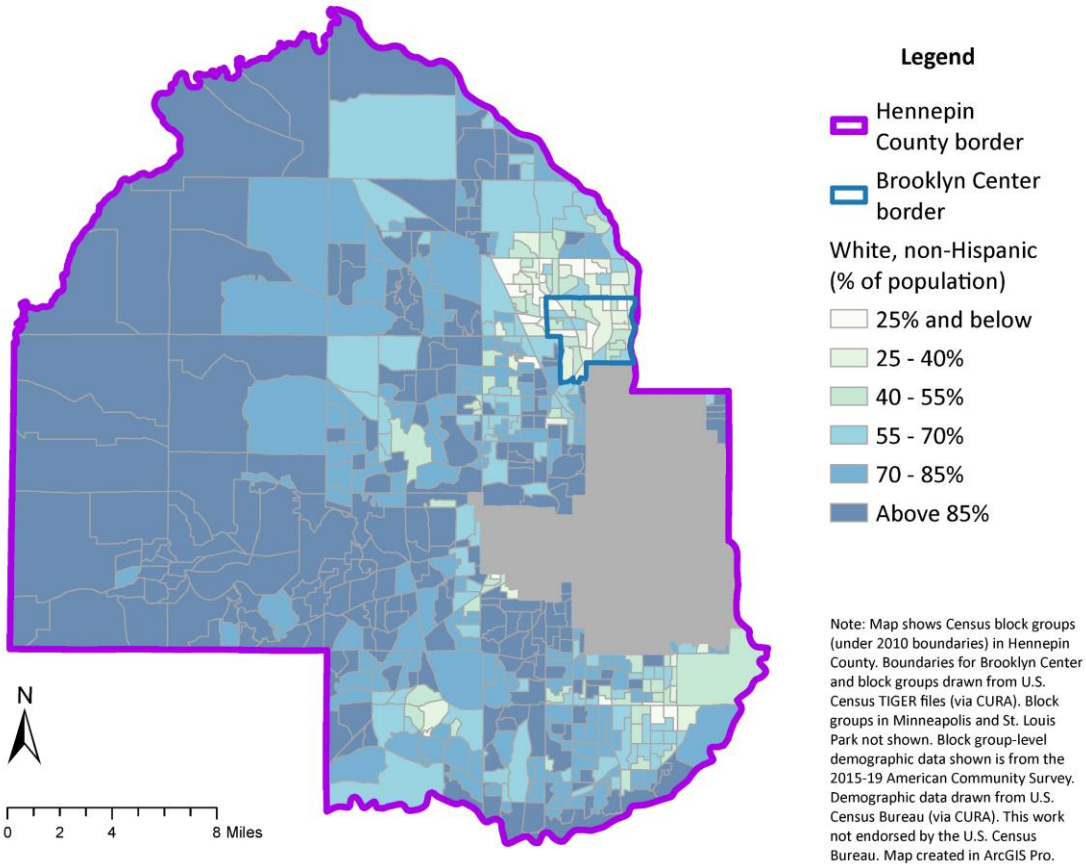
displacement, Raymond et al. (2022) linked block group-level eviction data with pre-treatment covariates from the 5-year ACS (Raymond et al., 2022). Wheeler et al. (2018) applied tract-level ACS 5-year data to examine the effects of spatial variation in housing demolition in Buffalo, New York (Wheeler et al., 2018, pp. 390, 399). In a recent example, Cassidy and Currie (2023) used ACS data by block group in their evaluation of a policy that expanded access to public defenders in New York City (Cassidy & Currie, 2023, p. 2).

One notable data cleaning choice was to restrict the panels by block group to those block groups without any manufactured home (mobile home) renters, and outside the top decile for the group quarters population. I refer to the sample excluding these block groups as the adjusted suburban sample. I removed block groups with mobile home renters from the analysis because these renters are entitled to unique pre-eviction protections that could confound an analysis of the effects of the Brooklyn Center ordinance (HOME Line Legal Staff, 2023). Removing block groups with manufactured home renters closes a possible backdoor path to causation, keeping the focus on the effects of Brooklyn Center's Tenant Protection Ordinance (Huntington-Klein, 2022). I limited the proportion of group quarters residents in order to mitigate concerns about unique dynamics for residents of institutions like colleges or prisons.

Descriptive statistics

As an initial step, I checked for the balance on covariates between block groups in Brooklyn Center and other areas of suburban Hennepin County. Mapping 2015-19 data by block group is an intuitive way to show whether the Brooklyn Center population differed from that of the rest of suburban Hennepin County. For example, **Fig. 4** below shows that block groups in Brooklyn Center tend to have lower white, non-Hispanic population shares than do block groups in other parts of suburban Hennepin County. Similar maps for other demographic characteristics are provided in **Appendix B**.

Fig. 4. White, non-Hispanic population share in suburban Hennepin County (2015-19 ACS).



Merritt and Farnworth (2021) found that, across the country, evictions tended to be concentrated in block groups with low white non-Hispanic populations (Merritt & Farnworth, 2021, pp. 569, 572). Of note, Brooklyn Center block groups tended to exhibit lower levels of educational attainment and lower median household incomes than block groups in other parts of the County. Broadly, analysis of pre-treatment covariates indicates that it is important to apply control variables when analyzing the effects of the Brooklyn Center ordinance, as there are a variety of demographic factors that likely influenced the path of eviction trends in Brooklyn Center.

Table 2 below shows selected descriptive statistics for Brooklyn Center and other parts of Hennepin County. Compared to the other parts of the suburban sample (described in the table as the suburban comparison areas), Brooklyn Center had a higher concentration of renters per occupied housing unit, a higher share of cost-burdened renters, and a higher share of renters of color. The table shows that Brooklyn Center has relatively similar demographic characteristics as Brooklyn Park. However, when compared to Brooklyn Park, Brooklyn Center has a higher share of renters per occupied housing unit, a lower annual rate of change in the number of rental housing units, and a higher share of Hispanic renters.

Table 2. Descriptive statistics regarding housing tenure and demographics, by geography within Hennepin County.

	Brooklyn Center	Brooklyn Park	Border Cities	Suburban Comp. Areas	Hennepin County
Population	30,849	80,068	117,511	745,987	1,245,837
Housing					
Occupied housing units	10,394	27,275	42,808	297,406	508,030
Renter-occup. units	4,087	7,716	12,141	83,538	191,183
Renter households (share)	0.379	0.283	0.284	0.275	0.369
Annual % change in renter-occupied housing units	0.201%	2.330%	0.706%	0.225%	0.716%
Cost-burdened (rent ≥ 30% income)	0.529	0.550	0.545	0.447	0.456
Rent ≥ $1,000 (2019 $)	0.606	0.603	0.587	0.699	0.610
Race (renter householders)					
White alone	0.347	0.303	0.424	0.668	0.630
Black alone	0.482	0.576	0.480	0.198	0.227
Asian alone	0.054	0.062	0.048	0.076	0.066
American Indian or Alaska Native	0.016	0.008	0.006	0.004	0.010
Other/multiple races	0.102	0.052	0.042	0.054	0.067
Ethnicity (renter householders)					
Hispanic, any race	0.144	0.071	0.068	0.066	0.075
White, non-Hispanic	0.287	0.255	0.376	0.631	0.594
Age (renter householders)					
Age 65+	0.117	0.097	0.158	0.205	0.148
Education (renter householders 25+)					
HS/equiv. or higher	0.839	0.872	0.884	0.926	0.900
Bachelor's or higher	0.157	0.152	0.169	0.387	0.413

Note: Demographic details focus on renter householders with various characteristics as a fraction of renter-occupied housing units, for the years 2015-19, unless otherwise indicated. Hennepin County Suburban Comparison Areas are defined as the portions of Hennepin County other than Brooklyn Center, Minneapolis, and St. Louis Park. Brooklyn Center is excluded to facilitate comparison, and Minneapolis and St. Louis Park are excluded since these cities adopted pre-eviction notice policies similar to that in the Brooklyn Center Tenant Protection Ordinance. Generally, values for the Suburban Comparison Areas were calculated by subtracting values for Brooklyn Center, Minneapolis, and St. Louis Park from the values for Hennepin County. The Border Cities are Brooklyn Park, Crystal, and Robbinsdale. Generally, values for the Border Cities were calculated by adding values for Brooklyn Park, Crystal, and Robbinsdale. Annual percent change in renter-occupied housing units calculated using figures in the 2017-21 and 2012-16 ACS 5-Year estimates (U.S. Census Bureau., 2021a, 2021c). Other data drawn from ACS 2015-19 5-Year Estimates (U.S. Census Bureau., 2021b).

In **Appendix B**, **Table B-1** shows that the application of inverse probability weights allowed for the construction of comparison groups that more closely approximated Brooklyn Center's demographic characteristics. For example, in the matched comparison groups the levels of median household income were much closer to that of Brooklyn Center. I used two versions of propensity score matching and applied inverse probability weights to generate the two comparison group options. The second approach used the same covariates that are applied in DiD models.

To account for unique circumstances for renters in subsidized housing, I checked for balance between Brooklyn Center and other areas of the sample using tract-level data from HUD's Picture of Subsidized Households. This was important because of unique protections for residents of federally subsidized units that Congress enacted during the pandemic. **Table B-1** shows that for the places with available data, the rate of publicly subsidized housing did not vary substantially between Brooklyn Center and the other areas of suburban Hennepin County. I did not include this covariate in the DiD models due to missing data concerns.

Next, I report descriptive statistics on eviction rates and eviction filing rates in Brooklyn Center and other parts of the adjusted suburban sample. **Table 3** below suggests that before and after the adoption of Brooklyn Center's ordinance, eviction rates and eviction filing rates did not increase by as much in Brooklyn Center as in the comparison group. Statistics reported in **Table 3** focus on average rates in 30-day periods, per 10,000 renter-occupied housing units. After conditioning on pre-treatment covariates, average monthly eviction rates increased from 5.191 to 6.759 per 10,000 renter households in Brooklyn Center, and increased from 4.551 to 8.438 per 10,000 renter households in the comparison group. The standard deviations are large, and the comparison between a single pre-treatment period and a single post-treatment period does not allow for analysis of policy effects that may have changed in size over time. In any case, it is notable that after Brooklyn Center adopted its ordinance (in a context when eviction filings were on the rise across the state), eviction rates in Brooklyn Center appear to have increased less dramatically than in the comparison group. Descriptive statistics provide an initial indication that Brooklyn Center's ordinance may have reduced eviction rates relative to what would have happened without the ordinance.

As opposed to relying on descriptive statistics, this paper uses two quasi-experimental methods—synthetic control and difference-in-differences—to assess whether the ordinance caused changes in eviction rates and filing rates. These quasi-experimental methods yield results that are broadly consistent with the descriptive statistics shown in **Table 3**. SC and DiD each provide suggestive evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods relative to what would have happened if Brooklyn Center had not adopted the ordinance.

Table 3. Statistics on average monthly eviction and filing rates, before and after the adoption of the Brooklyn Center Tenant Protection Ordinance.

	Brooklyn Center		Comparison Group	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
Eviction rate				
Mean rate	4.955	6.452	4.281	6.937
(SD)	(22.872)	(36.633)	(39.096)	(46.430)
Block groups	*22*	*22*	*402*	*402*
Observations	*88*	*176*	*1,608*	*3,216*
Eviction rate, inverse prob. weights applied				
Mean rate	5.191	6.759	4.551	8.438
(SD)	(23.390)	(37.473)	(23.516)	(35.842)
Block groups	*21*	*21*	*372*	*372*
Observations	*84*	*168*	*1,488*	*2,976*
Filing rate				
Mean rate	7.881	29.534	8.926	25.254
(SD)	(16.245)	(55.003)	(43.996)	(51.182)
Block groups	*22*	*22*	*450*	*450*
Observations	*88*	*176*	*1,800*	*3,600*
Filing rate, inverse prob. weights applied				
Mean rate	8.256	30.941	8.295	32.969
(SD)	(39.213)	(79.953)	(39.218)	(100.913)
Block groups	*21*	*21*	*399*	*399*
Observations	*84*	*168*	*1,596*	*3,192*

Note: Table shows mean eviction rates and eviction filing rates in Brooklyn Center and other areas of Hennepin County, for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Periods included here range from period -4 to period 7, corresponding to about 360 days from late 2021 to late 2022. Pre-periods are periods -4 through -1, and post-periods are periods 0 through 7. For evictions and filings, I report two sets of statistics: first, statistics for the adjusted suburban sample, and second, statistics for the adjusted suburban sample after applying inverse probability weights to construct comparison groups that more closely approximate Brooklyn Center. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. These are the same covariates used in DiD models. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate and filing rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. This analysis focuses on household-level evictions and eviction filings, aggregated into panels of evictions and filings by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Confidence about confidence intervals, triangulation, and the value of a two-pronged approach to causal inference

Using both SC and DiD to evaluate the effects of the Brooklyn Center ordinance allows for triangulation. Hammerton and Munafò (2021) contend that triangulation— "the thoughtful application of multiple…approaches, each with their own strengths and weaknesses"—can increase the plausibility of causal claims (Hammerton & Munafò, 2021, p. 575). In this section, I make the case that synthetic control and difference-in-differences have complementary strengths. When interpreting the policy relevance of the findings of this paper, I triangulate between SC and DiD. The two methods tell similar stories for policy effects on eviction rates, and are less consistent for other outcome variables (such as filing rates). When reporting suggestive evidence of causality, I restrict my discussion to eviction rates, since triangulation leads me to a higher level of confidence that estimates for eviction rates reflect true effects rather than statistical noise.

A main advantage of SC is that it takes a data-informed approach to the selection of comparison group units. Rather than using a comparison group chosen by the researcher in some arbitrary way, SC models use a transparent process to identify the places that will be compared to the treated unit (here, Brooklyn Center).[6] From a donor pool of cities, SC uses data from before the policy intervention to identify the most appropriate comparisons. I used suburban subdivisions of Hennepin County as the donor pool. Based on pre-COVID eviction trends and a variety of city-level covariates like race and renter cost burden, SC identifies a handful of cities that exhibited similarity to Brooklyn Center, and then produces a weighted average of their trends (e.g., their trend of eviction filing rates over time) (Huntington-Klein, 2022; Cunningham, 2021, pp. 511–512). The synthetic control trend can be compared visually to the trend for Brooklyn Center, allowing for an intuitive understanding of whether the policy made a difference. If the trend of the treated unit (evictions over time in Brooklyn Center) follows the trend of the synthetic control (the weighted average of certain donor pool units) in the period before the policy change, and then the trends diverge after the policy was adopted, then that can be interpreted as "suggestive" evidence of a causal effect (McClelland & Gault, 2017, p. 7).

While synthetic control has the advantage of allowing for causal inference in cases where there is one treated unit—like Brooklyn Center—in practice it is relatively challenging to use this method to make strong claims about causal effects. One problem has to do with the estimation of *p*-values. With a small pool of comparison cities, it is impossible to reach particularly precise estimates. Estimates of statistical significance are highly sensitive to choices like the amount of time to include in the panel and how to select and filter the donor pool (Cunningham, 2021, pp. 516–517). Here, the SC result that Brooklyn Center's ordinance had a significant effect on eviction rates is sensitive to whether Brooklyn Park is part of the donor pool (see **Appendix I**). A second problem for using synthetic control to study

[6] In one example, Abadie et al. (2015) used a donor pool of the sixteen OECD countries to construct a synthetic control for West Germany (Abadie et al., 2015). The authors used the comparison between West Germany and the synthetic West Germany to assess the effects of German reunification on GDP per capita (Abadie et al., 2015, p. 503). Out of the sixteen OECD countries, their synthetic West Germany assigned weights of 0 to eleven countries, and weighted Austria at 0.42, the United States at 0.22, Japan at 0.16, Switzerland at 0.11, and the Netherlands at 0.09 (Abadie et al., 2015, p. 502). The weights sum to one (McClelland & Gault, 2017, p. 6). Weighting the trends over time leads to figures that can show relatively clear breaks in trends, suggesting causal effects. The Abadie et al. figures show that the trends of GDP per capita were about the same for West Germany and the synthetic West Germany in the period leading up to German reunification, and then observed GDP per capita in West Germany fell below that of the synthetic West Germany (Abadie et al., 2015, p. 503). This difference in trends suggests reunification reduced West German GDP.

the Brooklyn Center ordinance is the inherent volatility of trends for rare events like evictions. This creates a challenge in constructing a panel that is coarse enough to show a meaningful trend over time.

One advantage of DiD is that it allows for analysis of treatment effects that are heterogeneous across groups. SC models use data aggregated at the level of the city, precluding analysis of variation in treatment effects between neighborhoods with different demographic characteristics. At the end of the DiD results section, I show two event studies calculated over samples partitioned by race and ethnicity. Policy effects are apparent in the places with more renters of color, and policy effects are not distinguishable from zero in the places with more white, non-Hispanic renters. Applying DiD on panels aggregated by block group made it possible to reach this finding.

A second advantage of DiD is that this method takes a more sophisticated approach to estimating statistical significance. In recent years it has become a best practice to report event study plots that show treatment effects by period, with confidence intervals that allow readers to see which estimates are statistically different from zero. In DiD, statistical significance is estimated in a more advanced way than in SC, reducing the sensitivity of claims about statistical significance to choices about which places to include in the comparison group. While SC models are sensitive to whether or not Brooklyn Park is in the donor pool, **Appendix Q** shows that DiD models are robust in specifications that restrict the comparison group, including a specification where Brooklyn Park is excluded.

Nonetheless, applying difference-in-differences event studies with one treated city presents a challenge regarding the estimation of standard errors and confidence intervals. To recover accurate estimates of standard error, there must be enough clusters of both treatment and comparison group units to allow for asymptotic validity (Roth et al., 2023, pp. 2236–2237). That is, without enough places that were subject to the policy, and places that were not, it may be unreasonable to make the assumptions necessary for meaningful estimates of uncertainty. Under certain conditions, Roth et al. suggest five could be a minimally appropriate number of clusters (Roth et al., 2023, p. 2237). But here there is just one treated city. It is possible to aggregate evictions by lower levels of geography. The Brooklyn Center borders happen to align with the 2010 boundaries of both Census tracts and Census block groups. This addresses the problem of asymptotic validity: in the adjusted suburban sample, there are 22 Brooklyn Center block groups and 402 comparison block groups.

This approach introduces new problems for the calculation of accurate confidence intervals. Subdividing the treated unit may lead to underestimates of standard errors, due to spatial correlation between small local areas within the same local government context. To mitigate concerns about underestimating standard error, I used bootstrapped standard errors for DiD models (Roth et al., 2023, pp. 2236–2238). Also, I tested for the sensitivity of results to the way I aggregated data across geography. In **Appendix S**, I report a robustness test for DiD using 2020 tract boundaries instead of 2010 block group boundaries. This test produces about the same result. However, there remain concerns about the accuracy of standard error estimates, so DiD results should not be understood to generate definitive evidence of causal effects.

The research questions at the core of this paper require a flexible approach to causal inference. As opposed to relying on descriptive statistics alone, I triangulate between synthetic control and difference-in-differences. Triangulation between SC and DiD boosts the plausibility of statements that point to causal conclusions. Synthetic control allows the researcher to compare trends over time, with the drawback that it does not apply a sophisticated procedure to estimate *p*-values. There are complex challenges regarding the implementation of DiD in a context with one treated unit. Acknowledging the

limitations of these methods, I triangulate between the two. When discussing policy implications, I elect to focus on eviction rates because SC and DiD told similar stories with respect to this outcome variable.

In subsequent sections of this paper I describe my approach to SC and DiD, and the corresponding results. In the discussion section, I attempt to pull together a coherent story about what these methods can tell us about the effectiveness of Brooklyn Center's ordinance. Through triangulation, I focus on how SC and DiD provide two lines of complementary (yet suggestive) evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods after its adoption.

Synthetic Control

Approach to synthetic control

As described above, I used most cities in Hennepin County as the donor pool. To boost the plausibility of the synthetic control model, I filtered the sample of Hennepin County cities down to a group that was more similar to Brooklyn Center. Using a smaller donor pool that has a greater degree of similarity to the treated unit limits the risk of bias (Abadie & Vives-i-Bastida, 2022, pp. 6–7). After removing St. Louis Park and Minneapolis due to their similar policies, the sample comprised Brooklyn Center and an initial donor pool of 43 other Hennepin County subdivisions.[7] Next, I filtered out cities with fewer than 50 renter-occupied housing units as of the 2015-19 ACS. This left 36 cities in the donor pool. I checked whether any remaining cities had substantial populations of renters in mobile homes. I restricted the sample to remove cities with more than 0.03 mobile home renters per renter-occupied housing unit. This choice resulted in excluding the cities of Corcoran, Dayton, Greenfield, and Shorewood. I also removed Medicine Lake from the sample due to data quality concerns. The remaining sample comprised Brooklyn Center and a donor pool of 31 other cities in suburban Hennepin County. All synthetic control models drew from this donor pool.

For SC, I aggregated data over twelve-week periods, with the February 28, 2022 policy adoption date at the start of period 31. SC requires data to exhibit "low volatility," as this is necessary to identify meaningful trends over time (Abadie & Vives-i-Bastida, 2022, p. 7). I tested several possible windows of time to include in each period. Aggregating data over four- and eight-week periods produced panels with relatively volatile trends. I decided to use panels of eviction data aggregated over twelve-week periods by city. This longer time period reduced the amount of volatility in eviction and eviction filing trends in the periods before policy adoption. SC requires a lengthy pre- period (Abadie & Vives-i-Bastida, 2022, p. 7). The panels used for SC models begin in 2015, allowing the use of data for the five-year period from 2015-19 to construct the synthetic control group. I used 2015-19 eviction data as well as a variety of city-level covariates from the 2015-19 ACS. The 2015-19 data used to train SC models were not affected by Brooklyn Center's ordinance or the unique circumstances of COVID-19.

With eviction data from 2015-23, covariates from 2015-19, and an ordinance adopted in 2022, there was an opportunity to use data from 2020 and 2021 as a validation period. Abadie and Vives-i-Bastida (2022) recommended leaving some pre-treatment data out of the model used to form the synthetic control (Abadie & Vives-i-Bastida, 2022, pp. 7–8). This allows for an intuitive check of whether

[7] All County subdivisions were cities, except for the Fort Snelling Unorganized Territory. For simplicity, I refer to the donor pool units as cities.

the model provides a plausible comparison for Brooklyn Center Accordingly, I did not train SC models using periods 23–30. I applied demographic covariates for periods 1-22 and the pre-treatment outcome variable trend for periods 13-22.[8] The validation period runs from period 23-30, and then the policy was adopted on the first day of period 31. The validation period allows for visual inspection of whether Brooklyn Center and the synthetic Brooklyn Center exhibited similar eviction dynamics from the start of 2020 until the adoption of the ordinance in February 2022. If Brooklyn Center and the synthetic Brooklyn Center do exhibit similar trends in period 23-30, that would suggest SC models provide plausible counterfactuals.

Synthetic control results

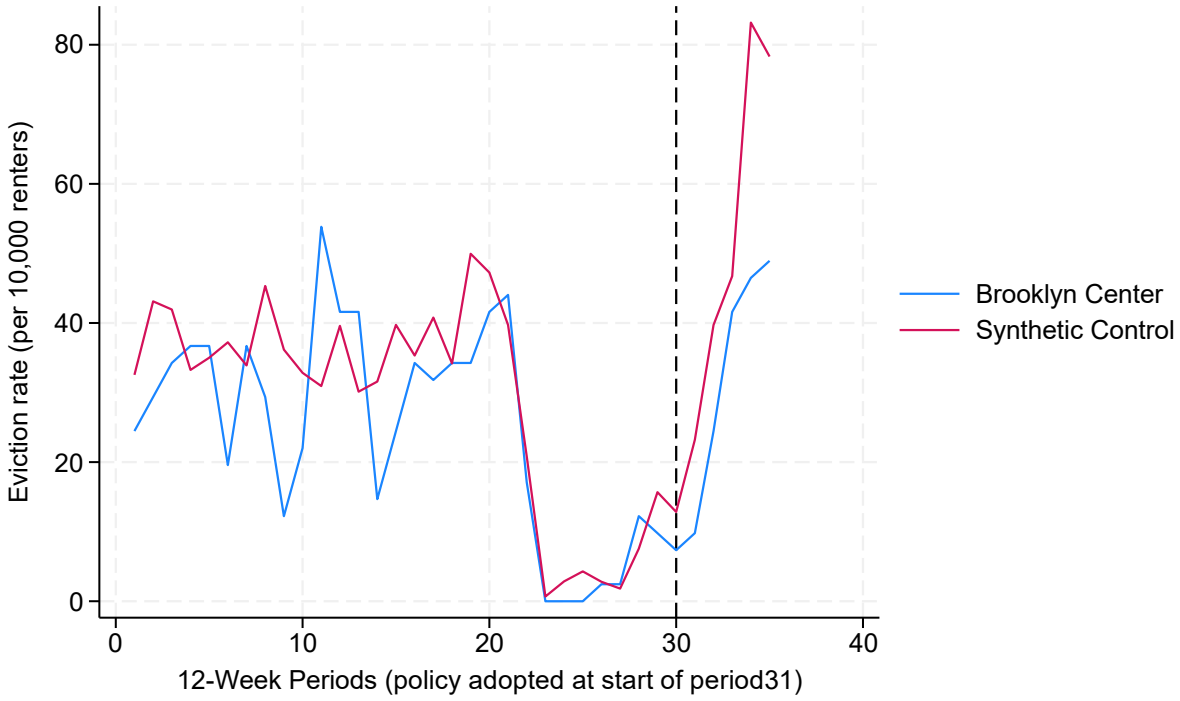
Synthetic control models tend to show the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods after policy adoption. For both eviction rates and filing rates, results disappeared when Brooklyn Park was excluded from the donor pool. Results for filing rates did not survive a placebo test with a fake treatment date. Results for eviction rates survived several placebo tests. So long as it is appropriate to include Brooklyn Park in the comparison group, there is suggestive evidence that the ordinance reduced eviction rates in some periods after policy adoption. (Descriptive statistics show that Brooklyn Park is indeed quite similar to Brooklyn Center.)

Eviction rates

Fig. 5 below provides suggestive evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates relative to similar Hennepin County cities in the period 37-48 weeks after policy adoption.

[8] It was important not to apply the outcome variable trend over all of the periods, so the other covariates could be part of SC models.

Fig. 5. Eviction rates, Brooklyn Center and Synthetic Control.

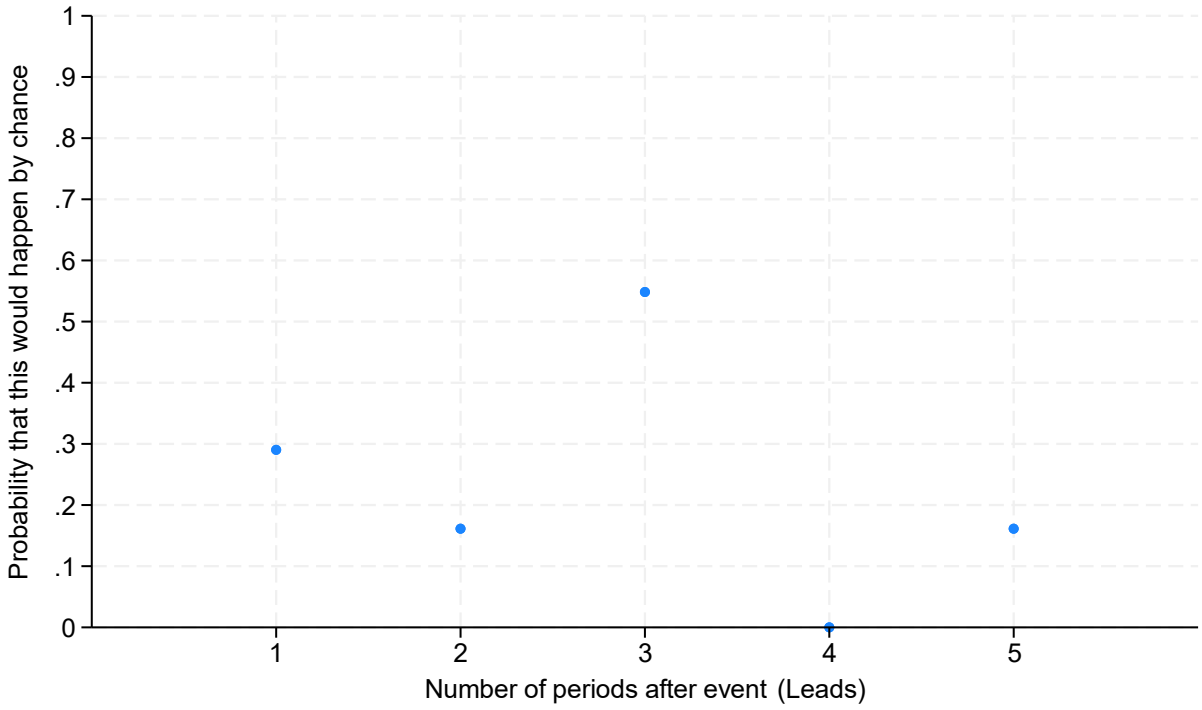


Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and New Hope. This model assigned weights of 0.519 to Richfield, 0.441 to Brooklyn Park, and 0.040 to New Hope. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer (Social Explorer & U.S. Census Bureau, 2023). Figure created using the *synth* Stata package developed by Abadie et al. (2020), as well as the *synth_runner* package developed by Galiani and Quistorff (2017) (Abadie et al., 2020; Galiani & Quistorff, 2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

This synthetic control model shows eviction rates per 10,000 renter-occupied housing units by city, before and after the adoption of Brooklyn Center's ordinance. Similar models, which add sequentially more of the control variables, are provided in **Appendix C**. The synthetic control model shown here as **Fig. 5** assigned weights to donor pool cities via a procedure incorporating the trend of eviction rates in periods 13-22, as well as a variety of control variables for periods 1-22 including race and ethnicity, the natural log of median household income, renter cost burden, and education (the specific controls are listed in italics in the notes beneath the figure). Covariates were only applied for the pre-COVID periods 1-22. The periods from 31 onward reflect the periods after policy adoption. The validation period, from periods 23-30, shows that the eviction trend in Brooklyn Center closely matches the trend for the synthetic Brooklyn Center, supporting the plausibility of using this model to estimate the counterfactual effect if Brooklyn Center had not adopted the ordinance.

There is a statistically significant effect in period 34, several months after the ordinance went into effect. I calculated standardized *p*-values by running placebo tests using each of the cities in the donor pool, and checking the fraction of the standardized effects from placebo tests that were as large or larger than the effect for Brooklyn Center in the relevant period (Galiani & Quistorff, 2017, p. 842). The standardized *p*-values for the five post-treatment periods (periods 31, 32, 33, 34, and 35) are shown in **Fig. 6** below. The standardized *p*-value of 0 in the fourth period after policy adoption (corresponding to period 34) indicates that no city in the donor pool had as large of a standardized effect in that 12-week period as did Brooklyn Center. For that period, Brooklyn Center's eviction rate was lower than that of the synthetic control, and this gap is statistically significant. Each period represents twelve-weeks, so there is suggestive evidence of a reduction in eviction rates in the period 37-48 weeks after policy adoption.

Fig. 6. Standardized *p*-values for synthetic control model of eviction rates (shown above).

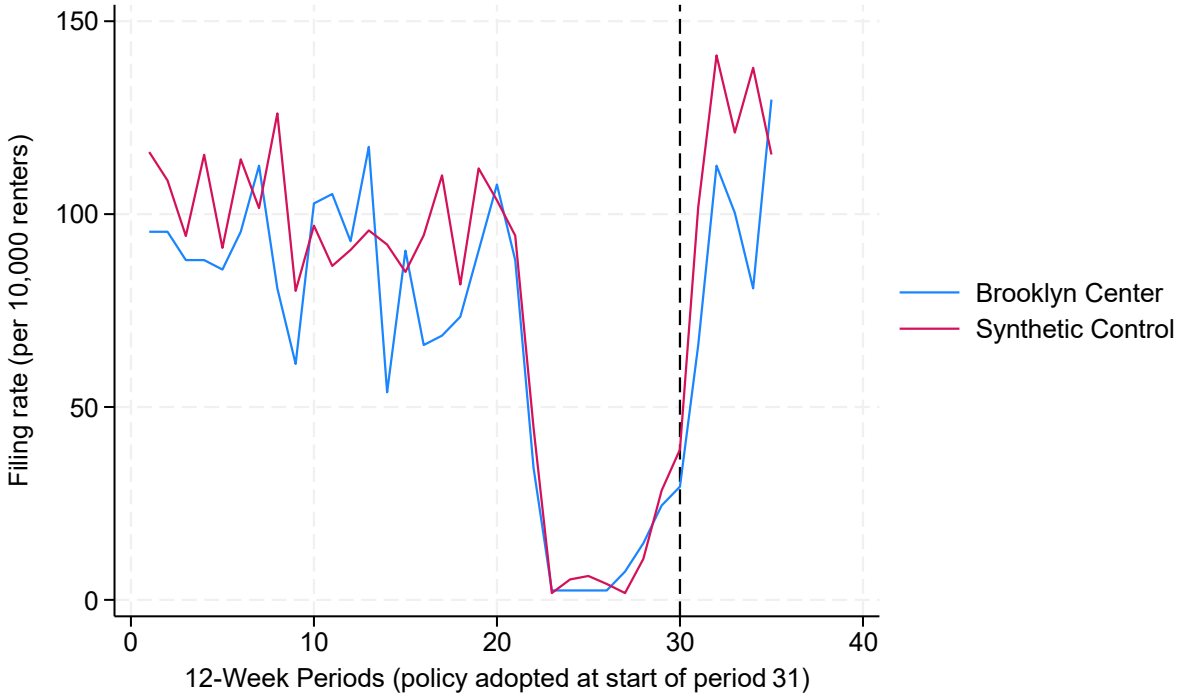


Note: Figure shows standardized *p*-values for a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and New Hope. This model assigned weights of 0.519 to Richfield, 0.441 to Brooklyn Park, and 0.040 to New Hope. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Filing rates

The main synthetic control specification for eviction filing rates indicates that in some periods after the adoption of the ordinance, Brooklyn Center had lower filing rates than did the synthetic Brooklyn Center. **Fig. 7** below uses the same covariates as the model in **Fig. 5**, but focuses on filing rates instead of the rate of cases with a judgment of eviction. A series of figures that sequentially add in control variables is presented in **Appendix D**.

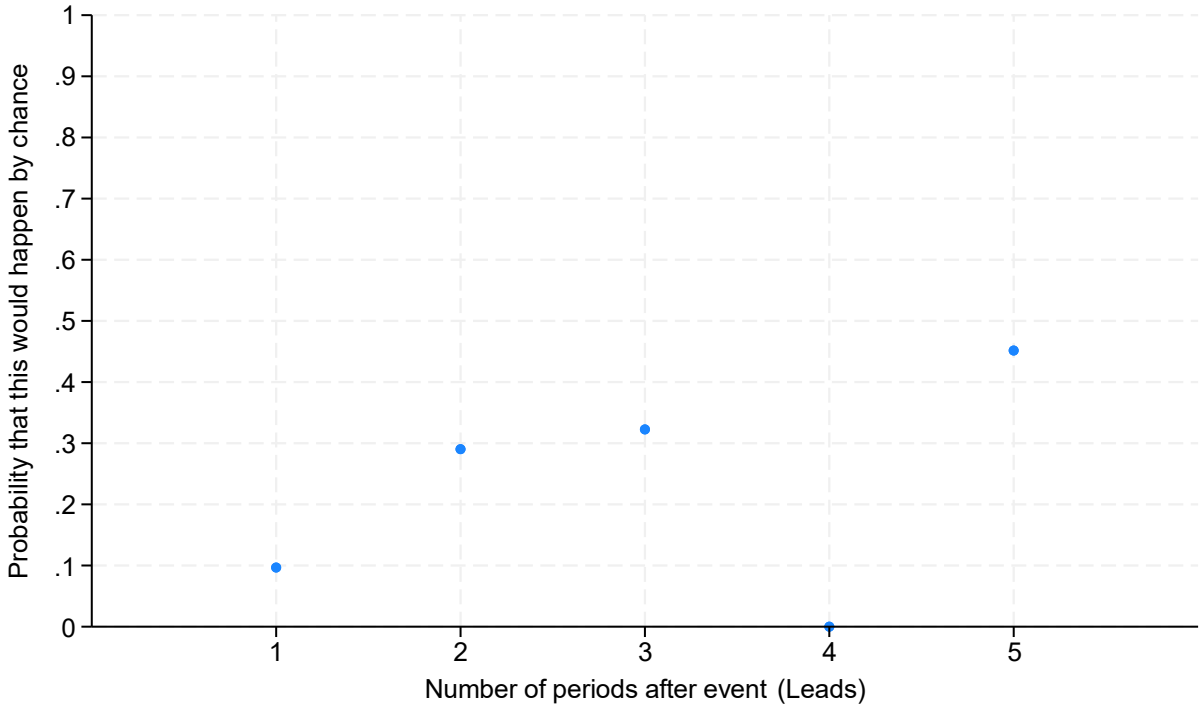
Fig. 7. Eviction filing rates, Brooklyn Center and Synthetic Control.



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and St. Bonifacius. This model assigned weights of 0.533 to Richfield, 0.455 to Brooklyn Park, and 0.013 to St. Bonifacius. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

As with eviction rates, the observed difference in eviction filing rates in period 34 is statistically significant. The corresponding standardized *p*-value (for the fourth post-treatment period) is shown in **Fig. 8** below.

Fig. 8. Standardized *p*-values for synthetic control model of eviction filing rates (shown above).



Note: Figure shows standardized *p*-values for a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and St. Bonifacius. This model assigned weights of 0.533 to Richfield, 0.455 to Brooklyn Park, and 0.013 to St. Bonifacius. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Other outcome variables

Focusing on the subset of cases that cited nonpayment of rent as the reason for the eviction action, there is evidence in some periods of apparent reductions in eviction and filing rates. Figures showing these results are provided in **Appendix E**. For nonpayment eviction rates, the standardized *p*-value was 0.032 in period 34, and above 0.1 for the other four post-treatment periods. For nonpayment filing rates, the standardized *p*-value was 0.065 in period 32, 0.097 in period 34, and above 0.1 for the other three post-treatment periods. SC models suggest that in some of the periods after the policy was adopted, the Brooklyn Center Tenant Protection Ordinance reduced the rate of eviction for nonpayment, and there is borderline evidence of an effect on the rate of eviction filings for nonpayment.

I also checked for effects on eviction case outcomes where the court's final judgment was something other than an eviction: dismissals, settlements, and tenant redemption. The relevant synthetic control specifications are provided in **Appendix F**. These outcomes could have allowed tenants to avoid displacement.[9] Tenant redemptions are rare, and synthetic control models exhibited excessively volatile trends. This precluded causal inference regarding the effects of the ordinance on tenant redemption rates. For dismissal and settlement rates, synthetic control models did not detect measurable differences after the ordinance went into effect (all standardized *p*-values were higher than the thresholds 0.05 and 0.1). I concluded there was not strong evidence the ordinance brought causal effects for dismissals, settlements, or tenant redemption.

Placebo tests and robustness checks for synthetic control

Placebo tests using a fake treatment date and only pre-COVID data

When SC models indicate apparent policy effects, it is possible to assess the plausibility of causal claims via sensitivity analysis and placebo tests (McClelland & Gault, 2017, pp. 7–8; Cunningham, 2021, pp. 524–525). One such placebo test to check whether the model would erroneously detect an effect when using a fake treatment date. I ran two placebo tests using only pre-COVID data, assigning a fake treatment date in period 17 and applying covariates in periods 1-16. These tests are in **Appendix G**. In the placebo test for eviction rates, zero of six standardized *p*-values were significant at either 0.1 or 0.05. This supports the viability of SC results for eviction rates. For the placebo test of eviction filing rates with a fake treatment date, one of six standardized *p*-values was less than 0.1 (and, indeed, less than 0.05). The result for filing rates is problematic, since a placebo test using only pre-treatment data and a fake treatment date erroneously detected a policy effect. This calls into question the reliability of the SC model for filing rates.

Placebo tests using Brooklyn Park, New Hope, and Richfield as fake treated units

I checked whether the main synthetic control specification would erroneously detect treatment effects when non-treated cities are defined as the treated unit. These figures are in **Appendix H**. I selected Brooklyn Park, New Hope, and Richfield, because these cities were assigned nonzero weights in various synthetic control specifications. For this set of placebo tests, Brooklyn Center is not included in the donor pool so as to remove its ordinance from consideration. The placebo tests using New Hope and Richfield as the treated city do not show treatment effects, as expected.

The placebo test that uses Brooklyn Park as the fake treated city (**Fig. H-1**) is more notable. Visually, this placebo test shows that the trend for Brooklyn Park was higher than the trend for the synthetic Brooklyn Park. To the extent this placebo test exhibits an erroneous treatment effect, that would be problematic for the reliability of the man SC specification for eviction rates. However, there is reason to believe this test is consistent with the reliability of the main SC specifications. None of the five post-treatment periods had *p*-values less than 0.1, as expected. Further, the trends of the synthetic Brooklyn Park prior to February 28, 2022 are rather volatile. This reduces the likelihood that we would erroneously conclude there was a causal effect for the fake treated city Brooklyn Park. So, none of the three placebo tests using fake treated cities contradicts the main SC specification.

[9] There is some ambiguity on the relationship between settlements and displacement.

Excluding Brooklyn Park from the donor pool

Given the unexpected dynamics surrounding Brooklyn Park, I checked whether the results were robust when excluding Brooklyn Park from the donor pool. They were not. Running the main specifications (again with Brooklyn Center as the treated unit), while removing Brooklyn Park from the donor pool, showed no apparent treatment effects. These figures are provided in **Appendix I**. Without Brooklyn Park as part of the comparison group, there does not appear to be a reduction in eviction or eviction filing rates after the adoption of the Brooklyn Center Tenant Protection Ordinance. Findings from synthetic control models are sensitive to whether Brooklyn Park is included in the donor pool.

Assessment of synthetic control results

SC models are relatively consistent for eviction rates. SC models showed a statistically significant reduction in eviction rates in the fourth twelve-week period after policy adoption. While the result for filing rates did not survive a placebo test using a fake treatment date, the result for eviction rates survived placebo tests using fake treatment dates and fake treated units. The result was sensitive to whether Brooklyn Park was included in the donor pool. This may not be problematic, as Brooklyn Park is demographically similar to Brooklyn Center.[10] Nonpayment cases seem to have been an important part of the story. For nonpayment cases, there was evidence of a reduction in the rates of eviction and eviction filings. For other case outcomes (like cases that settled), there was no evidence of policy effects. The most interesting finding here is that SC models provide evidence to suggest the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods after policy adoption. In the next section, I focus on whether DiD models confirm or contradict the evidence from synthetic control on eviction rates.

Difference-in-Differences

Approach to DiD event studies

As described earlier, in DiD models I used the adjusted suburban sample. Accordingly, DiD results should be understood to reflect the set of block groups in Hennepin County (excluding Minneapolis and St. Louis Park) without mobile home renters, and where the group quarters population share was outside the top decile (so, the population in each block group in the sample is comprised of no more than about 1.67% group quarters residents). The block groups outside Brooklyn Center are the comparison group. The second and fourth columns of **Table B-1** (in **Appendix B**) show that there are not large demographic differences between Brooklyn Center overall and the portions of Brooklyn Center included in the adjusted suburban sample.

[10] There is reason to believe Brooklyn Park is an appropriate comparison for Brooklyn Center. The summary statistics in **Table 2** show the cities are qualitatively similar. About 60% of housing units had rents above $1,000 in each city. 15.7% of Brooklyn Center renter householders 25+ had a bachelor's degree or higher, compared to 15.2% in Brooklyn Park. These two neighboring cities have been referred to as "the Brooklyns," reflecting the sense among some community members that Brooklyn Center and Brooklyn Park are rather similar places. Further, a 2015 report on evictions by the Minneapolis Innovation Team comments on the similarity of eviction dynamics in these two northern suburbs: "There is a stable geographic distribution of eviction judgments throughout the 2009 to 2015 period, with the largest concentration of cases in North Minneapolis, Brooklyn Center, and Brooklyn Park. This distribution aligns to demographic patterns, closely matching where non-white Hennepin county residents live" (Minneapolis Innovation Team, 2016, p. 21). However, Brooklyn Park and Brooklyn Center differ on certain pre-treatment covariates, most notably median household income by block group and the fraction of renter householders who are Hispanic. DiD models adjust for these covariates.

As an initial step, I analyzed pre-treatment block group-level data to check how closely Brooklyn Center block groups matched the demographic characteristics of other parts of sample. This analysis is presented in **Appendix B**. When comparing Brooklyn Center to other parts of the adjusted suburban sample, demographic differences are apparent for covariates including median household income, race and ethnicity, and education. These imbalances on observable characteristics pose a problem for the validity of the parallel trends assumption. If covariates that could affect the trend of the outcome variable differ substantially between Brooklyn Center and the comparison group, then it may be difficult to defend the parallel trends assumption (Sant'Anna & Zhao, 2020, p. 101). Demographic imbalances in the pre-period suggest there may have been time-varying dynamics that differed between Brooklyn Center and the comparison group. For example, eviction rates might be expected to increase by more over time in places with lower average income (e.g., after tenant protections expired, lower income families may have found it more and more challenging to pay rent on time).

To make it possible to defend the parallel trends assumption, I decided to proceed with a version of DiD that conditions on pre-treatment covariates. I tested whether it is possible to reach demographic balance between Brooklyn Center and other parts of the sample via an approach similar to propensity score matching. I found that propensity scores formed using pre-treatment covariates such as education and income can minimize differences between Brooklyn Center and the comparison group. This supports the viability of DiD after accounting for pre-treatment covariates.

The righthand columns in **Table B-1** show balance on covariates between Brooklyn Center and the comparison group after applying two versions of inverse probability weights. The weighting procedures generated comparison group options that were much more similar to Brooklyn Center's demographics. Focusing on the logistic propensity score approach, before applying weights the average median household income by block group was $62,040 in Brooklyn Center and $100,190 in the comparison group. After applying inverse probability weights via the logistic model, the average of median household income by block group was still $62,040 in Brooklyn Center, but fell to $62,924 in the comparison group. A gap of over $38,000 shrank to a gap of less than $900. By conditioning on covariates, there is less of a risk that time-varying dynamics would affect outcome variable trends in different ways for treated and untreated block groups.

Using the adjusted suburban sample, I conducted doubly robust difference-in-differences to account for pre-treatment covariates. This approach has been described by Sant'Anna and Zhao (2021) and Callaway and Sant'Anna (2021). Doubly robust DiD can produce valid estimates of treatment effects even when either the models of outcomes or the propensity scores are specified incorrectly (Sant'Anna & Zhao, 2020, p. 105; Callaway & Sant'Anna, 2021, p. 212). This makes it less problematic if DiD models incorporate an imperfect set of pre-treatment covariates.

Doubly robust DiD models like those in this paper depend on the conditional parallel trends assumption. To satisfy the identifying assumptions of DiD, the comparison group must exhibit parallel trends in the outcome variable, relative to Brooklyn Center, after conditioning on covariates. When discussing event study plots in the results section that follows, I show there is reason to believe the conditional parallel trends assumption holds.

<u>Recent advances in the DiD literature & the relevance of heterogeneity over time</u>

I do not report results for difference-in-differences estimated via two-way fixed effects because of the possibility that treatment effects varied over time. Until recently, researchers understood TWFE

models to recover the average treatment effect on the treated (subject to certain assumptions, including the parallel trends assumption). Indeed, from 2015-19 about 25% of highly cited papers in the *American Economic Review* applied TWFE (de Chaisemartin & D'Haultfœuille, 2023b, p. C1). To estimate an unbiased average treatment effect from TWFE, researchers must make an implausible assumption of homogeneous treatment effects ("the treatment effect should be constant, between groups and over time") (de Chaisemartin & D'Haultfœuille, 2023b, p. C2; Goodman-Bacon, 2021, p. 272). The assumption of homogeneous treatment effects is hard to defend.[11] Even without variation across groups, treatment effects often vary in intensity as time passes. Treatment effects from the Brooklyn Center Tenant Protection Ordinance may have fluctuated over time.[12] For example, the Brooklyn Center ordinance could have caused eviction rates to drop temporarily before bouncing back, or could have caused a gradual shift toward lower eviction rates as landlords and tenants adapted to the policy. It is important to take an approach to difference-in-differences that can account for time-varying effects, so TWFE is not appropriate.

DiD event study model, allowing for time-varying treatment effects

DiD event studies provide a pathway for causal inference in situations like that at hand, where treatment effects may vary over time. Sun and Abraham (2021) describe DiD event studies where, over multiple periods, treatments switch on at some point, and the treated units are compared to untreated units (Sun & Abraham, 2021, p. 177). In the DiD event studies in this paper, I use panel data on block groups in the adjusted suburban sample. The panel includes data on block group-level eviction rates in each of the last four 30-day periods before policy adoption, and in the first eight 30-day periods after policy adoption. For simplicity, I refer to these 30-day periods as months. The policy was adopted on February 28, 2022, defined as the first day of period 0.

Model 1 below allows for treatment effects that are heterogeneous over time. In **Model 1**, *ATT(t)* represents the average treatment effect on the treated in period *t*. *ATT(t)* is the difference between the treated outcome, $Y_1(t)$, and the counterfactual untreated outcome, $Y_0(t)$. This approach represents a specific case of the models described by Sun and Abraham (2021) and Callaway and Sant'Anna (2021), where all treated units switch into treatment at the same time (Callaway & Sant'Anna, 2021; Sun & Abraham, 2021, p. 177; Roth et al., 2023, p. 2226). The model allows treatment effects to vary by month; I essentially calculate a different ATT for each month after policy adoption. So, for example, *ATT(6)* is the average treatment effect on the treated in month number six.

$$ATT(t) = E[Y_1(t) - Y_0(t)] \quad \textbf{(1)}$$

Since I restricted the panel to the adjusted suburban sample—which includes 22 of Brooklyn Center's 26 block groups—all treatment effects should be understood to reflect neighborhoods in Brooklyn Center that do not have mobile home renters and that have no more than a small population share living in group quarters (institutional settings like hospitals).

[11] In some cases, TWFE can generate estimates of average causal effects that are positive, even when effects are negative within all periods of time considered (de Chaisemartin & D'Haultfœuille, 2020, pp. 2964–2965; Goodman-Bacon, 2021). In this paper, there is not a risk of making "forbidden" comparisons between already-treated units, since I focus on a cohort of block groups that were treated simultaneously, and compare to never-treated units (Roth et al., 2023, p. 2219).

[12] Visual inspection of eviction trends in Brooklyn Center and other parts of the suburban sample provide reason to believe there may be variation in the effect size in the months after the ordinance was adopted. This can be seen in the synthetic control models: eviction trends for both Brooklyn Center and various weighted averages of comparison cities rise and fall over time, and the gap between the trends seems to expand in the post-treatment periods.

There are a variety of potentially appropriate techniques to recover estimates of *ATT(t)*. De Chaisemartin and D'Haultfœuille's DID_M estimator can account for cases where treatment effects may vary over time (de Chaisemartin & D'Haultfœuille, 2023a, p. 2). Sant'Anna and Zhao (2020) proposed the doubly robust DiD estimator, which can be used to compare treated units to never-treated units (Sant'Anna & Zhao, 2020, p. 205). I elected to use the Callaway and Sant'Anna estimator in this analysis. This is a generalized version of the Sant'Anna and Zhao (2020) doubly robust DiD estimator (Callaway & Sant'Anna, 2021, p. 201; Sant'Anna & Zhao, 2020, p. 103). Implemented via the *csdid* Stata command, the Callaway and Sant'Anna DiD estimator can calculate the average treatment effect on the treated, for those units that began to receive treatment at the same time (Rios-Avila et al., 2021, p. 8). Although *csdid* is often used in cases of staggered timing, it can also estimate *ATT(t)* estimates in cases like that here where there is one point in time when treatment switched on. This approach has several advantages: *csdid* allows for the creation of easy-to-interpret event study plots, and this estimator can estimate doubly robust *ATT(t)*, conditioning on pre-treatment covariates that may affect outcome variable trends (Callaway & Sant'Anna, 2021, pp. 207, 212).

Tradeoffs around the specification choice: ordinary least squares (OLS) and negative binomial regression

The distribution of evictions by block group-month would lend well to negative binomial regression. **Appendix J** shows a histogram of evictions by block group-month in the panel used for DiD. The distribution is right skewed, and the most common number of evictions in a block group-month is 0. Since this analysis draws from comprehensive state administrative data, I make the assumption that the zero values are meaningful. If a block group had no evictions in a month, that would show up as a zero. When conducting regression analysis on evictions grouped at a small level of geography, negative binomial regression is appropriate because "the dependent variable is a count and overdispersion is a concern" (Goodspeed et al., 2021, p. 727).[13] Raymond et al. (2022) used negative binomial regression when analyzing block group-level data on evictions after disasters like hurricanes (Raymond et al., 2022, pp. 35–36, 44). Similarly, Goodspeed et al. (2021) used negative binomial regression in their analysis of tract-level eviction dynamics in Michigan (Goodspeed et al., 2021, p. 718). Goodspeed et al. contended that negative binomial regression was superior to ordinary least squares in this context, though their results would have been about the same if they had used from OLS (Goodspeed et al., 2021, p. 727).

While negative binomial regression has been used in the context of DiD, it is unclear how best to conduct DiD event studies via negative binomial regression after conditioning on demographic covariates (Fernandez & Jayawardhana, 2022, p. 1124; Chainey et al., 2021, pp. 1542, 1546–1547; Robin et al., 2021, p. 1171; Casey et al., 2018, p. 1). Recent advances in the DiD literature have largely neglected to account for cases where it may be most appropriate to use negative binomial regression. The Callaway and Sant'Anna (2021) DiD event study estimator allows for DiD after conditioning on covariates, but this estimator partly depends on OLS. OLS involves assumptions about variance that may not be appropriate in the present context. In short, there is a tradeoff between accurately modeling the data generating process, which would favor the use of negative binomial regression, and the practical need to conduct analysis using available software.

In **Appendix K**, I report two event study plots calculated via negative binomial regression. **Fig. K-1**, showing a negative binomial regression focused on eviction counts, suggests there were fewer

[13] For block group-months in the adjusted suburban sample, the mean of monthly eviction judgments was 0.102, the variance was 0.182, and the standard deviation was 0.427. The variance was higher than the mean, indicating that a negative binomial regression could be appropriate (Ford, 2023).

evictions in Brooklyn Center in two of the 30-day periods after the adoption of the ordinance. This figure does not show violations of pre-trends. The negative binomial DiD specification for eviction counts is consistent with the main results. **Fig. K-2**, focused on filing counts, has a significant pre-trend, indicating that the parallel trends assumption is likely violated in the post-period. However, the two negative binomial event study plots reported in **Appendix K** do not adjust for pre-treatment covariates.

Ideally, there would be a feasible way to blend negative binomial regression and doubly robust difference-in-differences. In the meantime, I focus on doubly robust DiD event studies calculated using OLS and conditioning on certain relevant pre-treatment covariates. Future research could examine how best to adjust for pre-treatment covariates when applying DiD in cases like this where the data generating process leads to overdispersion in the outcome variable, and where parallel trends may hold only after conditioning on covariates. For now, I caution that to the extent DiD results in this paper point toward causality, this evidence should be understood as suggestive and not definitive.

DiD identifying assumptions and the Brooklyn Center case

The key identifying assumptions in this case are (a) conditional parallel trends, (b) no anticipation, and (c) the stable unit treatment value assumption (SUTVA) (Roth et al., 2023, p. 2240; Sun & Abraham, 2021, p. 178). Since there is one treated cohort (all Brooklyn Center block groups were treated at the same time), and since *ATT(t)* allows for treatment effects that vary over time, it is not necessary to defend the strong assumption of homogeneous treatment effects (Sun & Abraham, 2021, p. 178).

Parallel trends and the conditional parallel trends assumption

DiD requires researchers to apply some version of the parallel trends assumption, depending on the specific form of DiD used. To account for covariate imbalance, I use doubly robust DiD and condition on block group-level pre-treatment covariates like education, income, and race and ethnicity. It is therefore necessary to defend the conditional parallel trends assumption (Sant'Anna & Zhao, 2020, pp. 101–102; Callaway & Sant'Anna, 2021, p. 219). Here, the conditional parallel trends assumption requires that when conditioning on covariates, the trend of potential outcomes (eviction rates) in Brooklyn Center would have followed the same path after the adoption of the ordinance as the observed outcome trend for the comparison group (Callaway & Sant'Anna, 2021, p. 219).

I checked whether the DiD models had significant pre-trend estimates (which would provide indirect evidence of a violation of parallel trends). In the DiD panels, with data aggregated data by block group in 30-day periods, the February 28 policy adoption date was the first day of period 0. Leaving out the last pre-treatment period as the reference, there were three remaining pre-periods to use when checking for violations of the parallel trends assumption. In the main DiD event studies for eviction rates and eviction filing rates, none of the pre-trends were significant. I also report the joint significance of the pre-trends. The pre-trends were not distinguishable from zero. The absence of individually or jointly significant pre-trends supports the viability of the conditional parallel trends assumption. Using data from before policy adoption, there is not evidence showing measurable differences between the paths of treatment and comparison group outcome variable trends. However, Roth (2022) cautions that such pre-trends tests often do not detect violations of parallel trends (Roth, 2022, p. 305). In addition, there is a potential for bias when restricting the analysis to those samples and model designs where pre-trends are not violated (Roth, 2022, pp. 305–306). It remains possible that there could have been time-varying dynamics that affected the paths of post-treatment outcomes differently for treatment and comparison group units. In any case, to avoid reporting on erroneous estimates of causal effects, I

restrict statements about policy implications to those models where there is not evidence to contradict the conditional parallel trends assumption.

No anticipation assumption

A second identifying assumption for DiD event studies is no anticipation (Sun & Abraham, 2021, p. 178). Under no anticipation, treatment effects cannot begin until after the time of treatment; nobody began to respond to the policy in advance. There are some potential concerns here. I address these concerns by focusing on the policy adoption date as opposed to the date of policy implementation.

In this research, the no anticipation assumption could have been violated if property owners in Brooklyn Center had advance knowledge of the ordinance, and accordingly made anticipatory decisions about how to approach eviction cases. There is some reason to believe this occurred. Brooklyn Center held a variety of City Council and Housing Commission meetings to discuss the proposed ordinance in the months prior to its adoption (Agenda: City Council Meeting, 2022). These discussions may have alerted landlords to the potential that some version of a tenant protection policy would be implemented in the near future. Further, there was a gap of just over a month between the adoption of the ordinance on February 28, 2022 and the date it went into effect in early April. Anticipatory effects could have played out in a few different ways. First, landlords could have tried to get ahead of the ordinance, initiating eviction cases earlier than they might have otherwise. Second, landlords may have adhered to the policy earlier than required, due to a misunderstanding about when the new requirements would go into effect. In short, there were possible violations of the no anticipation assumption.

To mitigate concerns about the no anticipation assumption, I used the policy adoption date as the date when the policy switched on (instead of using the policy implementation date in early April). De Chaisemartin & D'Haultfœuille (2023) proposed that in cases with concerns about the no anticipation assumption, using the policy adoption date can "immunize[]" against anticipatory effects (de Chaisemartin & D'Haultfœuille, 2023b, p. C18).[14]

Spillovers and SUTVA

DiD research typically proceeds under the stable unit-treatment value assumption (SUTVA) (Roth et al., 2023, p. 2240). SUTVA requires that potential outcomes for a particular unit are unaffected by the treatment status of other units (that is, that there are no spillovers between units that could affect outcomes) (Boesche, 2022, p. 15; Roth et al., 2023, p. 2240; Holland & Rubin, 1988; Rubin, 1974). The kinds of treatment that could plausibly create a concern about spatial spillover effects are different from those I am analyzing here. Butts (2021) described how changes in the housing supply like the construction of new buildings could affect surrounding neighborhoods, resulting in a spatial spillover effect that could confound comparisons that exploit variation in the distance from construction (Butts, 2023, p. 1). Unlike the effects of newly constructed buildings on surrounding areas, the effects of city eviction policies are sharply constrained by city borders. Owners of properties in Brooklyn Center are

[14] Using February 28 as the date of treatment addresses another challenge: ambiguity about whether the policy went into effect on April 4 or April 9, 2022. Public materials released by the City of Brooklyn Center were contradictory on this point, potentially leading to confusion among property owners about the specific time when the policy switched on (City of Brooklyn Center, 2022a, 2022b). I reached out to city staff asking for clarification, and did not receive a response. Aggregating data across 30-day periods addresses this concern, as both April 4 and April 9 fall in the same period (the second 30-day period after policy adoption). *ATT(t)* estimates for the second post-treatment period (where $t = 1$, since the policy was adopted on the first day of period 0) can be interpreted as the treatment effect for the period when the policy was implemented.

required to follow the city's housing policies, and owners of properties outside Brooklyn Center are not required to do so. Property owners do not have an incentive to comply with regulations from other jurisdictions. It does not seem likely that a new city policy regarding the eviction filing process in one city would have a spillover effect that changed how landlords handled eviction cases in neighboring cities. If there are other concerns about spillovers, the ordinance would have been most likely to influence outcomes for comparison group units in immediate geographic proximity to Brooklyn Center. In **Appendix Q** I report robustness checks showing I would get about the same results if I excluded the cities adjacent to Brooklyn Center from the sample.

DiD results

Through DiD event studies, I found some suggestive evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates and eviction filing rates in some periods after policy adoption. There was mixed evidence regarding effects on eviction rates for nonpayment. The topline result, for eviction rates, survived a variety of robustness checks (including a test for whether policy effects remained measurable when Brooklyn Center was removed from the sample). Broadly, DiD event studies for eviction rates are consistent with the results from synthetic control.

Eviction rates

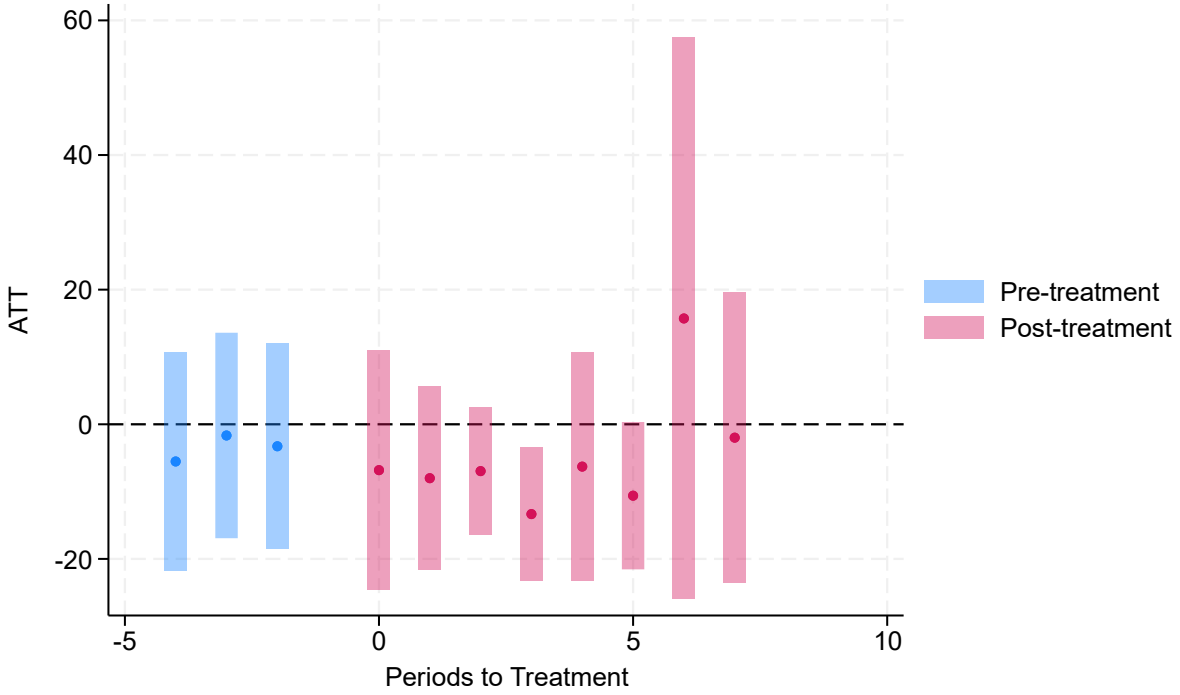
Table 4 and **Fig. 9** below show an event study focusing on eviction rates per 10,000 renter-occupied housing units, comparing Brooklyn Center to the rest of the adjusted suburban sample. This model conditions on block group-level pre-treatment covariates including the natural log of median household income, the share of renter households that are cost burdened, and the share of renter householders who are white non-Hispanic (the full list of covariates is listed in italics in the notes below the table and figure). The three pre-trend coefficients have confidence intervals that include 0, providing indirect support for the conditional parallel trends assumption. The pre-trends are not jointly significant, with a joint *p*-value of 0.904. This indicates no difference in outcome variable trends prior to treatment between Brooklyn Center and the comparison group. One of the eight *ATT(t)* estimates is statistically significant at the 5% level, and two are significant at the 10% level, indicating that Brooklyn Center's ordinance may have reduced eviction rates in some periods after its adoption. This is more than we would expect due to random chance (with eight tests, given no effect, we would expect on average that 0.4 tests would be significant at the 5% level, and that 0.8 tests would be significant at the 10% level). Seven of the eight *ATT(t)* estimates are negative, and the one positive estimate also has the largest standard error. The estimate for period 3 (the fourth 30-day period after policy adoption), *ATT(3)*, is -13.340. The corresponding *p*-value is 0.011. In this period, there is statistically significant evidence that the ordinance reduced eviction rates by 13.340 evictions per 10,000 renter-occupied housing units. While the average is not significant, for the first eight 30-day periods after policy adoption the monthly eviction rate was lower in Brooklyn Center by 4.79 evictions per 10,000 renter-occupied housing units. The standard errors are largest in the last two periods, indicating that the estimates are less precise as time passes.

Table 4. Event study, eviction rates per 10,000 renter-occupied housing units.

	Estimate	SE	*p*-value
Pre-trend estimates			
Joint significance			*0.904*
Period -4	-5.522	7.378	0.454
Period -3	-1.662	3.956	0.674
Period -2	-3.263	6.653	0.624
ATT(t) estimates by period			
Average	*-4.785*	*5.629*	*0.395*
ATT(0)	-6.814	9.118	0.455
ATT(1)	-8.007	6.733	0.234
ATT(2)	-6.956	6.276	0.268
ATT(3)	-13.340	5.247	0.011
ATT(4)	-6.288	8.367	0.452
ATT(5)	-10.608	5.681	0.062
ATT(6)	15.720	27.222	0.564
ATT(7)	-1.985	11.247	0.860
Observations	4,716		

Notes: Table reports difference-in-differences event study focusing on eviction rates, showing joint significance of pre-trends, pre-trend estimates, average ATT, and *ATT(t)* for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap, tidycensus, OpenStreetMap, and Google Maps API (Kahle, 2023; Walker & Herman, 2023; OpenStreetMap Foundation, 2023; Google Maps Platform, 2023). Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Fig. 9. Event study, eviction rates in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample.



Note: Figure shows difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Filing rates

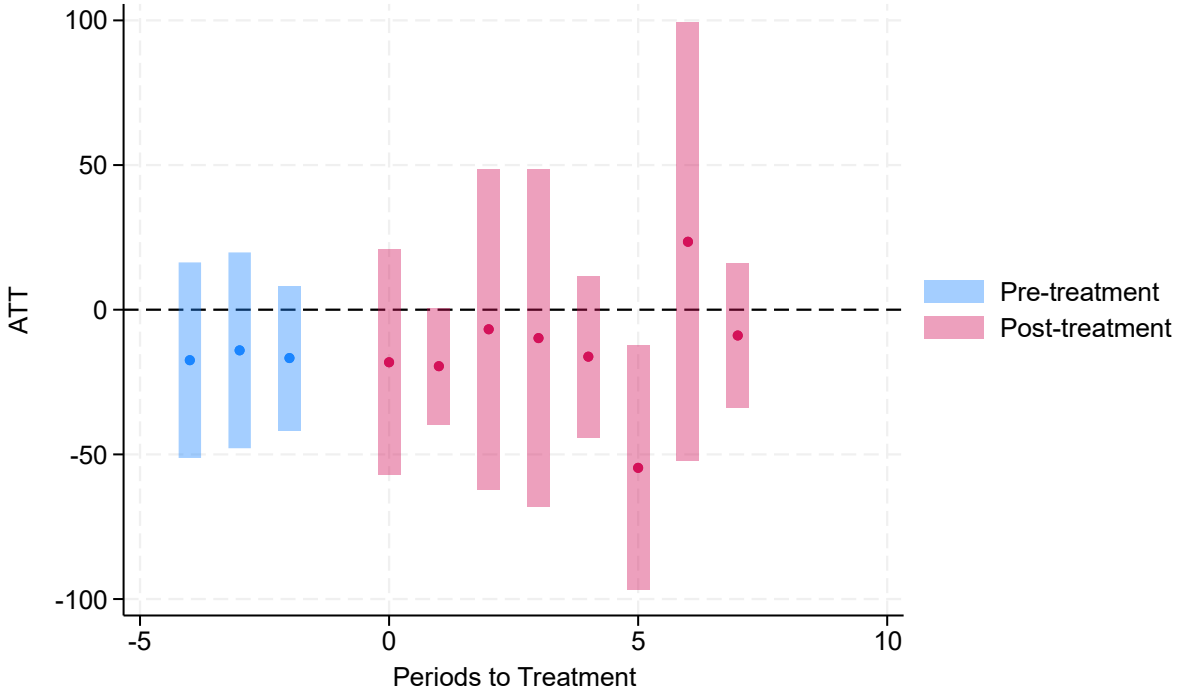
Table 5 and **Fig. 10** below apply the same covariates, this time focusing on eviction filing rates. None of the pre-trend coefficients is significant, supporting the viability of parallel trends. The pre-trends are jointly insignificant. One of the eight *ATT(t)* estimates is statistically significant at the 5% level, and two are significant at the 10% level. This result suggests the ordinance brought a reduction in eviction filing rates in some periods. As for eviction rates, the average period-specific treatment effect is negative (though not significant), and seven of the eight period-specific treatment effect estimates are negative. In period five, there is statistically significant evidence that the ordinance caused Brooklyn Center's eviction filing rate to be lower than that of the comparison group by 54.650 filings per 10,000 renter-occupied housing units.

Table 5. Event study, eviction filing rates per 10,000 renter-occupied housing units.

	Estimate	SE	*p*-value
Pre-trend estimates			
Joint significance			*0.382*
Period -4	-17.442	18.935	0.357
Period -3	-14.040	18.959	0.459
Period -2	-16.700	12.845	0.194
ATT(t) estimates by period			
Average	*-13.811*	*14.999*	*0.357*
ATT(0)	-18.152	20.278	0.371
ATT(1)	-19.514	10.462	0.062
ATT(2)	-6.755	24.635	0.784
ATT(3)	-9.805	25.114	0.696
ATT(4)	-16.214	14.370	0.259
ATT(5)	-54.650	21.794	0.012
ATT(6)	23.495	39.826	0.555
ATT(7)	-8.895	12.985	0.493
Observations	5,040		

Note: Table reports difference-in-differences event study focusing on eviction filing rates, showing joint significance of pre-trends, pre-trend estimates, average ATT, and *ATT(t)* for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction filing rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level eviction filings, aggregated into a panel of eviction filings by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Fig. 10. Event study, eviction filing rates in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample.



Note: Figure shows difference-in-differences event study, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction filing rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level eviction filings, aggregated into a panel of eviction filings by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Nonpayment

Event studies focusing on eviction rates for nonpayment were sensitive to the particular control variables applied. Two alternate specifications, shown in **Appendix L**, lead to some ambiguity as to whether there was a measureable reduction in the rates of eviction for nonpayment after the adoption of the ordinance. The figure with the same covariates as above did not show any significant *ATT(t)* estimates. The model with coarser controls showed some significant negative coefficients. The sensitivity of the results for nonpayment indicates the evidence here is not conclusive.

Placebo tests and robustness checks for DiD

Checking for expunged cases

Expunged cases could confound an analysis of the effects of the Brooklyn Center Tenant Protection Ordinance. If cases were expunged, those records would not appear in data drawn from the Minnesota court system. To check this possibility, I used records of eviction filings collected by HOME Line as part of its Eviction Letters project. HOME Line is a nonprofit that advocates for Minnesota renters (*Free Legal Help for Renters*, 2023).[15] Through the Eviction Letters Project, HOME Line tracks statewide eviction filings. The Eviction Data Assistant pulls data from the Minnesota state court system on a daily basis, and cross checks the data each week and each month to add any cases that might not have been captured by the first pass. For each eviction filing, HOME Line records information including the date the case was filed and the tenant's address. Since HOME Line collected eviction data at the time of filing, it is likely that the organization's records would include cases that were eventually expunged and therefore hidden from the court records that I accessed later on via CURA.

I ran a difference-in-differences event study specification using as the outcome variable the difference in eviction filing rates between HOME Line and CURA data. This variable was designed to capture information about filings that had disappeared from court records by July 2023. I began by geocoding HOME Line filing data in ArcGIS Pro. I aggregated these data by block group and 30-day period. I then subtracted the count of eviction filings in the court system data from the count of eviction filings in HOME Line data, for each block group-month. Next, I calculated the difference per 10,000 renters. In a DiD event study using the difference in filing rate as the outcome variable, I did not detect any significant pre-trends or *ATT(t)* estimates. So, I did not detect evidence to suggest the ordinance changed the rate of expunged cases in Brooklyn Center relative to the adjusted suburban sample. The corresponding event study plot is shown in **Appendix M**.

Alternate data source for filing rates

I checked whether the DiD results for filing rates were robust when using eviction data from HOME Line as opposed to CURA. This result is shown in **Appendix N**. Essentially, **Fig. N-1**—an event study for filing rates using HOME Line data—shows the same result as **Fig. 10** above (which used CURA data on filings). Using HOME Line data, there was not evidence of a violation of parallel trends, and there was a significant negative *ATT(t)* estimate for period 5. The size of the effect in period 5, when calculated with HOME Line data, lies within the confidence interval of the estimate for that period calculated with CURA data. DiD results for filing rates were robust across these two data sources.

Placebo tests using a fake treatment date

This placebo test, shown in **Appendix O**, used the same period as the other panels for DiD, however the placebo treatment date is in a period several months after the policy was actually implemented. This placebo test shows a significant pre-trend, indicating that using this fake treatment date led to a violation of the parallel trends assumption. This placebo test did not erroneously detect any treatment effects, supporting the validity of the main results. It would have been problematic if a test with a fake treatment date had detected an apparent policy effect.

[15] Disclosure: I consulted with HOME Line as part of my research process.

Placebo tests using nearby cities as fake treated units

One key check on the validity of DiD results is to run placebo tests for whether the model would erroneously detect effects for units did not adopt the policy of interest (Cunningham, 2021). **Fig. P-1** in **Appendix P** is a placebo test with Brooklyn Park as the treated unit. This was estimated using the adjusted suburban sample but excluding Brooklyn Center. This placebo test does not erroneously detect any significant *ATT(t)* estimates, supporting the plausibility of the main results. In a similar placebo test, I used block groups with centroids in cities adjacent to Brooklyn Center as the fake treated unit.[16] I again removed Brooklyn Center from the sample. This test (shown in **Appendix P** as **Fig. P-2**) also supports the credibility of the main DiD specification, since it does not erroneously detect treatment effects.

Excluding nearby cities from the sample

I tested whether the DiD result for eviction rates is robust when nearby cities are excluded from the adjusted suburban sample. It is, as shown in **Appendix Q**. The first figure, **Fig. Q-1**, is an event study where block groups with centroids in any of the cities adjacent to Brooklyn Center (Brooklyn Park, Crystal, and Robbinsdale) are excluded from the sample. **Fig. Q-2** is an event study where block groups in Brooklyn Park are excluded from the sample. In these event studies, none of the pre-trends are significant, supporting the viability of parallel trends. Both figures show a significant negative estimate of *ATT(t)* for period 5. This is consistent with the main results. Regardless of whether nearby cities are included in the comparison group, in at least one period after policy adoption there was evidence of a reduction in eviction rates. DiD results are robust to the exclusion of neighboring cities like Brooklyn Park from the comparison group.

This suggests the results would survive even if we had modified the sample to reduce the influence of spillovers. If Brooklyn Center's ordinance led to spillovers, we might expect to see unique dynamics in cities bordering Brooklyn Center. This robustness check shows we would get about the same result if we restricted the comparison group to cities with less geographic proximity to Brooklyn Center.

Restricting the sample to block groups with at least 100 renter households

I also checked whether the results might be driven by unique dynamics in block groups with small renter populations. With small renter populations, there could be misleading statistics on renter demographics. In this robustness check, I ran the main specification using only those block groups with at least 100 renter-occupied housing units. The results survived: the pre-trends are still insignificant, and there was one significant negative *ATT(t)* estimate. I report this event study plot in **Appendix R**.

Using an alternate method to aggregate data across geography

The Modifiable Areal Unit Problem (MAUP) could confound difference-in-differences models with data aggregated by block group. Under MAUP, "fine-scale predictions based on aggregated data change based on how the data is aggregated geographically" (Arambepola et al., 2022, p. 2). Local geography is continuous: walking down the street, a neighborhood might seem to remain about the same on either side of an arbitrary boundary like that of a Census block group (Calderón-Figueroa et al., 2022, p. 1). Imposing categories like block group boundaries allows for analysis of demographic

[16] These cities are Brooklyn Park, Crystal, and Robbinsdale.

differences between small local areas. But policy analysis is challenging when aggregating data over levels of geography where the boundaries are arbitrary and can change over time (Prouse et al., 2014, p. 61). One approach to validate statistical analysis of neighborhood-level data is to conduct robustness checks with alternate aggregation methods, such as by using a larger or smaller geographic level (Blair et al., 2022, p. 1363; Prouse et al., 2014, pp. 63–64; Yang et al., 2023, p. 2).

A second potential problem for DiD models is the ecological fallacy. Arambepola et al. (2022) defined the ecological fallacy as situations where correlations "at the aggregate level may not hold on a fine scale" (Arambepola et al., 2022, p. 2). This could be a problem for analysis of eviction dynamics for Brooklyn Center, to the extent associations between covariates are sensitive to the choice to aggregate by block group (Landis & Reina, 2021, p. 321). It is possible that observed correlations between variables like median household income and eviction rates would be different if data had been aggregated in a different way.

To test whether the results are sensitive to data aggregation choices, I report a robustness check on DiD models where I aggregated by Census tracts under 2020 boundaries (instead of 2010 block groups). Tracts are generally larger, including several adjacent block groups. Since the boundaries of tracts and block groups change every ten years, it is possible to re-run the analysis using boundaries set in 2020 instead of 2010. For this test I applied tract-level covariates from the 2017-21 ACS.

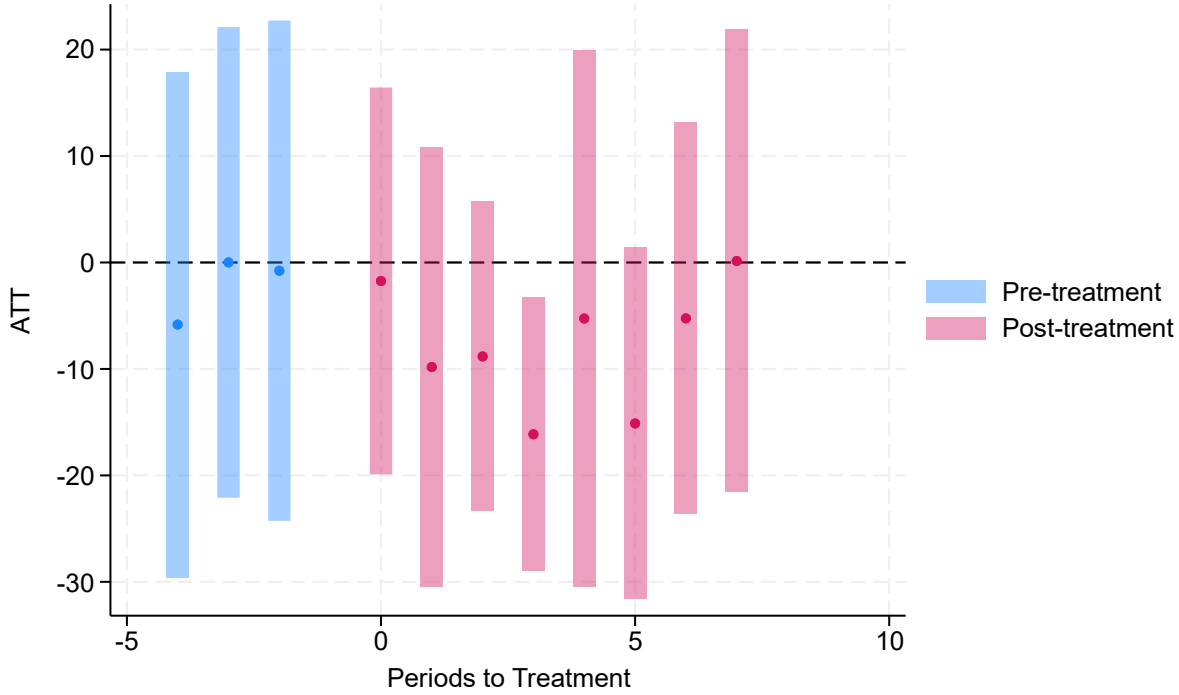
The DiD model for eviction rates survived this robustness check. When aggregating evictions with 2020 tract boundaries instead of 2010 block groups, there were no significant pre-trend coefficients, and there was a significant negative *ATT(t)* estimate for period 5 after treatment. This was consistent with the main result: there was evidence of reduced eviction rates in some periods after policy adoption. The corresponding event study plot is presented in **Appendix S**. The result here provides an indication that DiD results are robust to choices of how to aggregate data across space.

<u>Partitioning the sample by race and ethnicity</u>

Partitioning the sample by race and ethnicity, I checked whether apparent policy effects varied between neighborhoods with different demographic characteristics. This test revealed that to the extent the ordinance reduced eviction rates (in some periods), this effect was concentrated in the parts of Brooklyn Center where more of the renters are people of color.

Fig. 11 below focuses on places with more renters of color. This event study focuses on eviction rates, over the part of the adjusted suburban sample restricted to block groups where less than 50% of renter householders are white, non-Hispanic. For these block groups with more renters of color, there was a significant negative *ATT(t)* estimate for one of the periods after treatment. This is similar to the pattern observed in the main DiD specification.

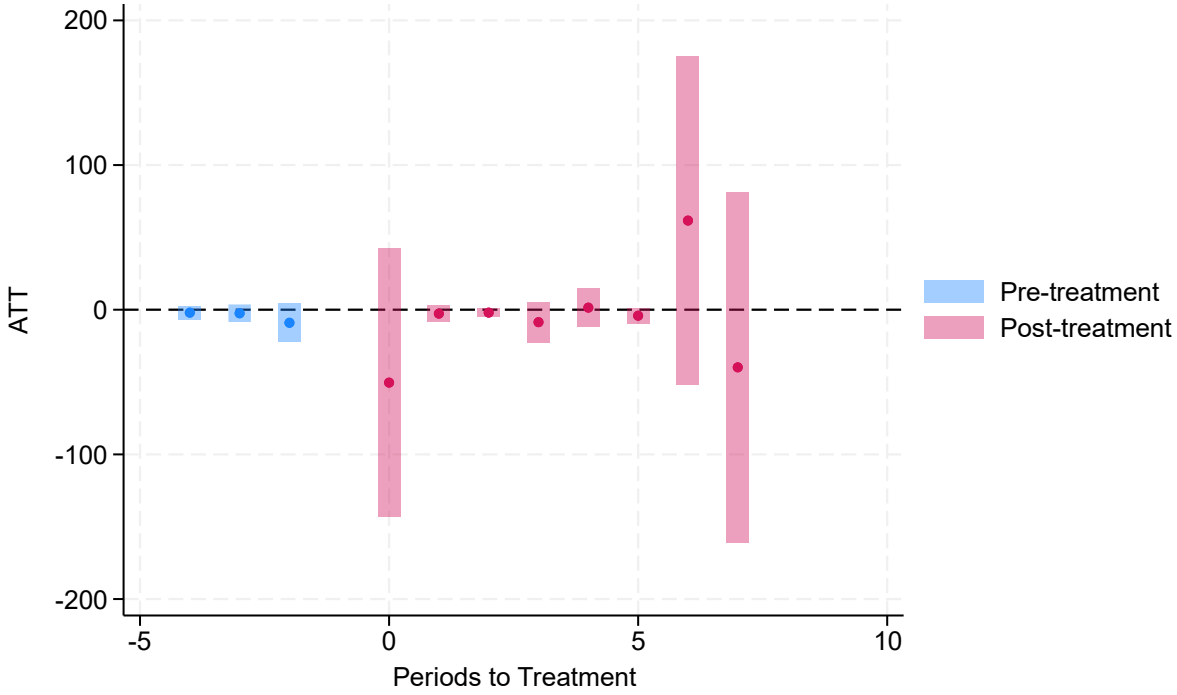
Fig. 11. Partitioned results, event study using block groups with higher shares of renters of color.



Note: This figure uses a partitioned sample, focusing on block groups with a higher share of renters of color. Figure shows difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Block groups excluded if 50% or more of renter householders were white non-Hispanic. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

By contrast, when focusing on places where renters are mostly white non-Hispanic, there was not a significant treatment effect in any period. This result is provided in **Fig. 12** below.

Fig. 12. Partitioned results, event study using block groups with higher shares white non-Hispanic renters.



Note: This figure uses a partitioned sample, focusing on block groups with a higher share of white non-Hispanic renters. Figure shows difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Block groups restricted to those where 50% or more of renter householders were white non-Hispanic. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

When partitioning the sample, DiD only provides evidence to suggest a policy effect on eviction rates in the neighborhoods with more renters of color. The presence of measurable treatment effects (in some periods) for block groups with more renters of color, and the absence of treatment effects for the block groups with mostly white non-Hispanic renters, indicates that to the extent the policy brought reduced eviction rates this benefit was concentrated in areas with more renters of color. Available data do not allow for definitive conclusions about effects for individual renter households by race and ethnicity.

Discussion

As described in the empirical strategy section, in this paper I seek to reach causal conclusions by triangulating between two quasi-experimental methods. Addressing the limitations of synthetic control and difference-in-differences, when discussing policy-relevant conclusions I focus on the outcome variable where results were relatively consistent across research designs and model specifications: eviction rates. This analysis produced suggestive evidence that the Brooklyn Center Tenant Protection Ordinance reduced eviction rates in some periods after it was adopted. Evidence was mixed as to whether these effects remained substantial over time. Evidence was less consistent for other outcome variables like eviction filing rates. For eviction rates, the synthetic control model detected a significant negative effect in the period 37-48 weeks after policy adoption. Across a variety of specifications, DiD models detected significant negative effects in some earlier 30-day periods. DiD models had wide confidence intervals, especially for the last few periods.

The upshot from synthetic control is that there is some suggestive evidence that Brooklyn Center's ordinance caused reduced eviction rates in the period 37-48 weeks after policy adoption. Synthetic control has the advantage of showing intuitive differences in trends between Brooklyn Center and several similar Hennepin County cities. The main drawback of the synthetic control approach is that it applies rudimentary procedures to estimate standard error, precluding strong statements about statistical significance. In addition, the synthetic control models presented in this paper were rather sensitive to specification choices. For example, SC models for eviction rates only detect an effect when Brooklyn Park is included in the donor pool.

Through DiD, I found additional suggestive evidence that the ordinance reduced eviction rates in some periods after adoption. DiD specifications were robust to a variety of specification choices, such as a test where I aggregated data by tract instead of block group. These tests tended to support the credibility of the results. But there were important ways that DiD was a flawed tool to estimate treatment effects in this context. First, it may have been more appropriate to use negative binomial regression given the distribution of evictions by block group-month. Future research could address the challenge of adjusting for covariates when applying DiD with a negative binomial approach. Second, applying DiD models to evaluate a policy adopted by just one city required aggregating data at levels lower than where treatment was assigned (by block group instead of by city). This may have produced incorrect estimates for confidence intervals. With the limitations of applying DiD in this case, it would be inappropriate to understand DiD results as more than suggestive evidence of policy effects. As discussed below, future research on policies like the Brooklyn Center Tenant Protection Ordinance could provide more clarity about possible causal effects.

One direction for future research on eviction prevention would be to implement difference-in-differences to evaluate the effects of tenant protection policies. Researchers could focus on a nationwide sample of states or cities that have adopted particular types of tenant protections like just cause. There may be an opportunity to use DiD with staggered timing, focusing on changes before and after the state- or city-level adoption of particular policies. Future DiD analysis of policies like the Brooklyn Center Tenant Protection Ordinance could take steps similar to those used in this paper to ensure there is reasonable balance between the treatment and comparison groups on the demographic characteristics of local renters. Doubly robust DiD, as developed by Callaway and Sant'Anna (2021), offers a promising approach to implement DiD when there is reason to believe parallel trends may hold only after conditioning on pre-treatment covariates. Future work could also split the sample into cohorts of places with higher and lower population shares by race and ethnicity. Focusing on a larger sample of

government entities (where many places did and did not adopt particular tenant protection policies) would address some of the empirical limitations of this paper.

To facilitate future research in this area, local governments could implement policies to track the issuance of pre-eviction notices. Publicly accessible data on the issuance of pre-eviction notices could make it easier to quantify how often tenants and landlords resolve disputes before reaching the point where the landlord decides to file an eviction action in court.

A second direction for future research would be to use qualitative methods to investigate tenant experiences of housing discrimination. I found some evidence to suggest that the Brooklyn Center ordinance primarily reduced eviction rates in the parts of the city where higher shares of renters are people of color. Perhaps, just cause protections made it more challenging for Brooklyn Center property owners to engage in discriminatory behavior when deciding whether to renew leases. Pre-eviction notice requirements may have made it more challenging for landlords to engage in arbitrary decision-making about which tenants to evict. Future research could address the limitation that this paper's methods do not allow for direct analysis of whether the ordinance changed the likelihood of housing discrimination. Such a question might be possible to address through qualitative methods and a comparative case study approach. Abadie et al. (2015) proposed that researchers could use synthetic control to inform qualitative research, applying quantitative models to select appropriate geographic comparisons for jurisdictions of interest (Abadie et al., 2015, p. 396). The synthetic control models used in this paper indicate that qualitative researchers could focus on these three cities as comparisons for Brooklyn Center: Brooklyn Park, New Hope, and Richfield. Using qualitative methods to study tenant experiences in places like Brooklyn Center, compared to tenant experiences in places like Brooklyn Park, New Hope, and Richfield, could shed light on how the presence or absence of just cause protections might connect to experiences of housing discrimination.

While more research is always welcome, the consistency of results for eviction rates provides a basis to reach policy-relevant conclusions about the most likely effects of the Brooklyn Center ordinance. Contributing to a growing literature on evictions, this paper provides suggestive evidence that the Brooklyn Center Tenant Protection ordinance reduced the eviction rate in some time periods.

Policies like pre-eviction notice and just cause may be viable tools for policymakers seeking to reduce the likelihood that community members will be evicted. Past research has demonstrated that evictions cause increased homelessness and hospital use, and may decrease employment for some groups (Collinson et al., 2023). To the extent policies like Brooklyn Center's ordinance prevent eviction, this likely brings direct benefits to the people who might otherwise experience displacement and homelessness, with possible indirect benefits for taxpayers (who contribute to the cost of emergency room care and unemployment insurance). Prior work has shown that evictions are disproportionately common for Black and Hispanic people (Hepburn et al., 2020; Evans et al., 2019). This paper has a notable implication for racial justice: the Brooklyn Center Tenant Protection Ordinance may have functioned to mitigate longstanding disparities. The benefit of reduced displacement seems to have been concentrated in areas with more renters of color.

During the COVID-19 pandemic, the U.S. federal government temporarily banned most evictions. When COVID-era tenant protections started to expire, eviction filings spiked across the state of Minnesota starting in late 2021. At the local level, in early 2022 the City of Brooklyn Center adopted a Tenant Protection Ordinance that included just cause protections and pre-eviction notice requirements. The best evidence suggests that Brooklyn Center's ordinance flattened the eviction curve.

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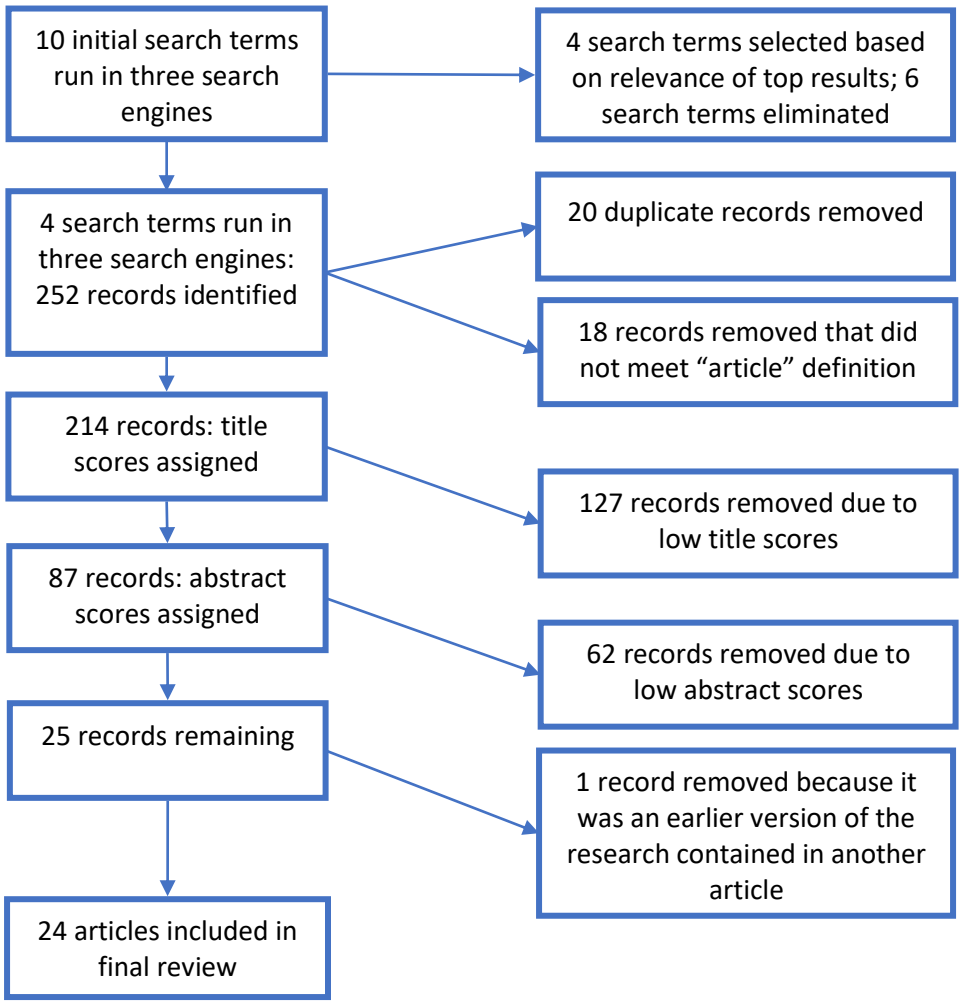
Appendices

Appendix A: Systematic literature review

To identify appropriate methods, the systematic literature review, I set inclusion criteria before beginning to review articles. I proceeded through a structured process to identify a final list of 24 articles that I reviewed in detail. The literature review process is shown as a flow chart in **Fig. A-1** below.

Fig. A-1. Systematic literature review flow chart



Inclusion criteria

Results meet the Inclusion Criteria if and only if all the following criteria are true:

1. The result is an article, defined as a peer-reviewed journal article, book chapter, or report published by a non-profit organization, think tank, or university.

2. The article was published in the year 2000 or later.

3. The article is substantially focused on the landlord-tenant relationship.
    a. If the article describes other topics in detail, that is acceptable so long as there is thorough analysis related to the landlord-tenant relationship.

4. The article is substantially focused on the United States.
    a. If the article describes other countries in detail, that is acceptable so long as there is thorough analysis related to the United States context.

5. The article is substantially focused on causal analysis of public policy.
    a. If the article contains other kinds of information, that is acceptable so long as there is a thorough engagement with questions of causality. For this purpose, causal research includes randomized controlled trials, quasi-experimental research, impact evaluations, program evaluation reports, and qualitative analysis of how or why policies lead to certain outcomes.

6. The article presents information gathered via clearly specified research methods.

Procedure

I identified ten initial search terms and three search engines that appeared to be likely to provide relevant material: the University of Minnesota Libraries, Policy Commons, and the PAIS Index. I ran these initial search terms in each search engine, and then ranked the search terms by the fraction of the search results that appeared likely to meet the inclusion criteria. The final search terms focused on quasi-experimental and qualitative methods of evaluating landlord-tenant policies.

I proceeded with the list of final search terms, and ran them in each of the three search engines. After applying filters and eliminating duplicates and records that did not appear to be journal articles or similarly rigorous research products, I had 214 records remaining. To narrow the list of articles to a manageable level, I assigned scores to the article titles, eliminating those that did not appear likely to meet the inclusion criteria. Of the remaining articles, I assigned scores to the article abstracts, and kept only those that appeared to be very likely to meet the inclusion criteria. Ultimately, I identified 24 articles to review in detail.

List of initial search terms for literature review

a. evict AND “impact evaluation”
b. evict AND “quasi-experimental”
c. evict AND “qualitative”

d. landlord-tenant AND “impact evaluation”
e. landlord-tenant AND “quasi-experimental”
f. landlord-tenant AND “qualitative”
g. “pre-eviction notice” AND “impact evaluation”
h. “pre-eviction notice” AND “quasi-experimental”
i. “pre-eviction notice” AND “qualitative”
j. evict AND “cure” AND “notice” AND “evaluation”

List of final search terms

a. evict AND “cure” AND “notice” AND “evaluation”
b. evict AND “qualitative”
c. landlord-tenant AND “impact evaluation”
d. landlord-tenant AND “quasi-experimental”

Analysis of final articles

I identified common features in the final 24 articles (shown in **Table A-1** below). 10 used some form of quasi-experimental approach. Of these, the most common approaches were instrumental variables (4 articles) and difference-in-differences (3 articles). 10 articles used qualitative content analysis, mostly in connection with stakeholder interviews.

DiD has comparative advantages over the other methods identified in the literature review. Instrumental variables approaches require the identification of an instrument that is correlated with an outcome of interest and uncorrelated with potential confounding variables. In practice, it is uncommon to identify such an instrument. Qualitative approaches are well-suited for understanding the process by which programs produce outputs, but do not allow for causal claims.

The systematic review provided suggestive evidence that the DiD method was the best option for evaluating Brooklyn Center’s Tenant Protection Ordinance. In two of the three DiD articles identified in the literature review, researchers focused on local policy interventions related to rental housing, and compared outcomes of interest in the treated locality with other places that had not adopted such a policy (Collinson & Ganong, 2018, pp. 82–83; Yeon et al., 2022, p. 3212). This approach appeared promising in the current research, as I was able to obtain data on eviction cases in Brooklyn Center as well as other areas in Hennepin County, Minnesota.

Table A-1. Final list of articles.

Article No.	Author(s)	Year	Title	Main methods
1	Patricia A. Baird	2004	Analysis of Landlord/Tenant Mediation & Disparate Impact Towards Low-Income People	Survey
2	Douglas N. Evans and Jeremy R. Porter	2014	Criminal history and landlord rental decisions: a New York quasi-experimental study	Audit study
3	Robert Collinson et al.	2022	Eviction and Poverty in American Cities	Instrumental variables
4	Rose Wang Tan et al.	2020	Essays in Housing and Experimentation [first chapter: "Effects of Foreclosures on Homeowners, Tenants, and Landlords"]	Instrumental variables; propensity score matching
5	AJ Golio et al.	2022	Eviction Court Outcomes and Access to Procedural Knowledge: Evidence From a Tenant-Focused Intervention in New Orleans	Survey-weighted logistic regression
6	Jihwan Yeon et al.	2020	Examining the impact of short-term rental regulation on peer-to-peer accommodation performance: a difference-in-differences approach	Difference-in-differences & triple difference
7	National Coalition for the Homeless et al.	2009	Foreclosure to Homelessness 2009: The Forgotten Victims of the Subprime Crisis	Qualitative analysis of surveys
8	Erika Raquel Marquez	2015	Health impact assessment of proposed rental housing policy within Clark County, Nevada, USA	Mixed methods including qualitative analysis of interviews
9	Robert Collinson and Peter Ganong	2018	How Do Changes in Housing Voucher Design Affect Rent and Neighborhood Quality?	Difference-in-differences; time series
10	Stephanie Casey	2020	Investigating the Causes and	Spatial regression;

Article No.	Author(s)	Year	Title	Main methods
	Pierce		Consequences of Eviction	instrumental variables
11	Kirstin Peterson Frescoln	2019	Making Public Housing Work: Examining the Implementation and Impacts of a Work Requirement in Public Housing	Qualitative analysis of interviews
12	Andrew J. Greenlee	2014	More Than Meets the Market? Landlord Agency in the Illinois Housing Choice Voucher Program	Qualitative analysis of interviews
13	Kelsi Gabrielle Hobbs	2021	On the Prevalence and Prevention of Rental Housing Evictions	Multiple regression; systematic literature review
14	Danielle Vaclavik et al.	2018	Permanent Housing Placement and Reentry to Services Among Family Recipients of Homelessness Prevention and Rapid Re-Housing Program (HPRP) Assistance	Logistic regression; Cox proportional hazards models
15	Eva Rosen	2014	Rigging the Rules of the Game: How Landlords Geographically Sort Low-Income Renters	Ethnography
16	Marco Brydolf-Horwitz	2020	Risk, Property Rights, and Antidiscrimination Law in Rental Housing: Toward a Property-in-Action Framework	Ethnography
17	Anna C. Reosti	2018	Tenant Screening and Fair Housing in the Information Age	Mixed methods including online field experiment and interviews
18	Bryan P. Wade	2009	The effectiveness of the Advocacy and Benefits homeless programs in reducing homelessness or at-risk for homelessness	Surveys

Article No.	Author(s)	Year	Title	Main methods
19	Rebecca Diamond, Timothy McQuade, and Franklin Qian	2018	The Effects of Rent Control Expansion on Tenants, Landlords, and Inequality: Evidence from San Francisco	Difference-in-differences; instrumental variables
20	Patrick J. Fowler and Michael Schoeny	2015	The Family Unification Program: A Randomized-Controlled Trial of Housing Stability	Longitudinal randomized controlled trial
21	Douglas N. Evans, Kwan-Lamar Blount-Hill, and Sebastian Hoyos-Torres	2021	The Frontline of Housing Access: Comparing Criminal Stigma among Landlords and Real Estate Agents in New York	Audit study
22	Brianna Simone Anderson	2022	The Individual and Joint Effects of State-Level Landlord-Tenant Policy on Mobility among Renters	Multivariate probit regression
23	D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Hennessy	2013	The limits of unbundled legal assistance: a randomized study in a Massachusetts District Court and prospects for the future	Randomized controlled trial
24	Garrett L. Grainger	2021	Yielding Returns on Homeless Policy Through the Micro-Economisation of Housing First Recipients	Nonparticipant observation; qualitative analysis of interviews

Appendix B: Balance on covariates between Brooklyn Center and other parts of suburban Hennepin County

Using 2015-19 data, I checked for demographic balance between Brooklyn Center and other parts of suburban Hennepin County. First, I report a series of maps showing covariates by block group in suburban Hennepin County. These maps are **Figs. B-1** through **B-6**. The maps show that Brooklyn Center diverges from other parts of the County on certain potentially relevant covariates, such as levels of educational attainment. Second, **Table B-1** shows descriptive statistics for block groups in Brooklyn Center as well as various comparison group options. This table provides an indication that synthetic control and difference-in-differences are viable despite observable demographic imbalances between Brooklyn Center and other parts of suburban Hennepin County. Descriptive statistics for two matched comparison groups are similar to statistics for Brooklyn Center. Using other portions of the adjusted suburban sample of Hennepin County, and conditioning on certain pre-treatment covariates, it is possible to construct a comparison group that approximates Brooklyn Center's observable demographic characteristics.

Fig. B-1. Renter-occupied housing units as a share of occupied housing units in suburban Hennepin County (2015-19 ACS).

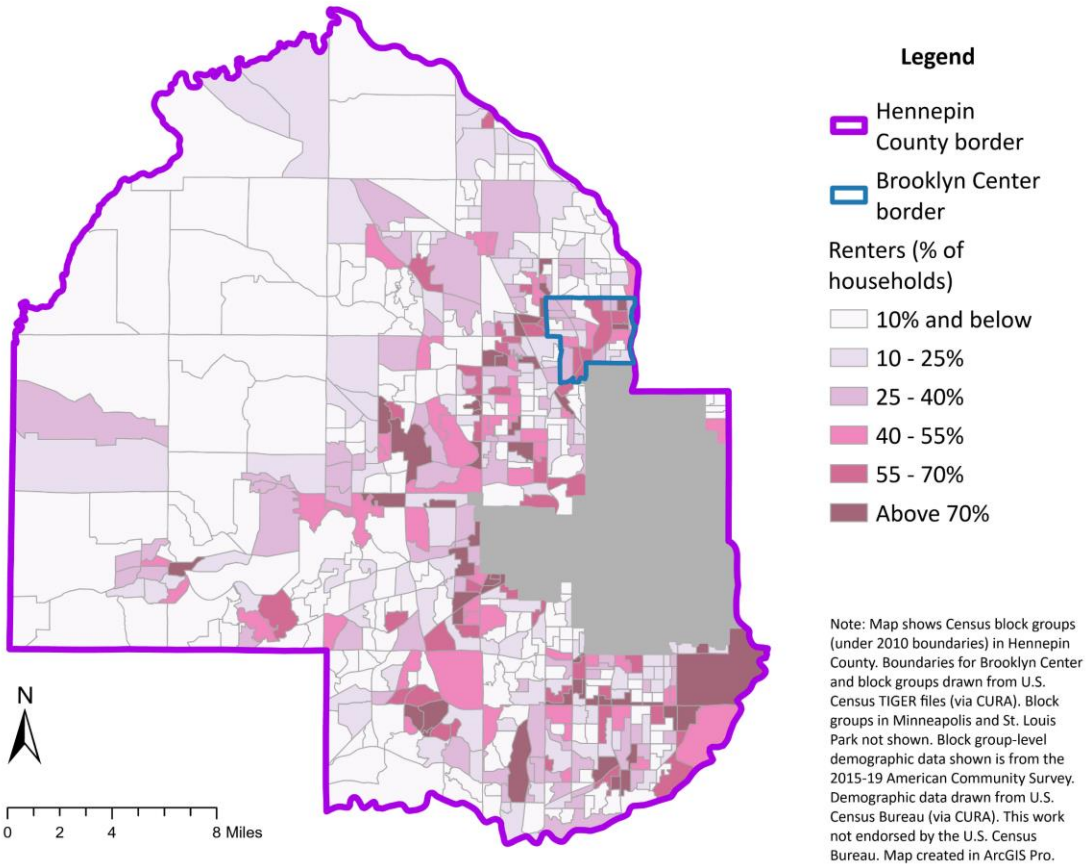


Fig. B-2. Highest educational attainment is less than high school (or equivalent) as a share of the population 25+ in suburban Hennepin County (2015-19 ACS).

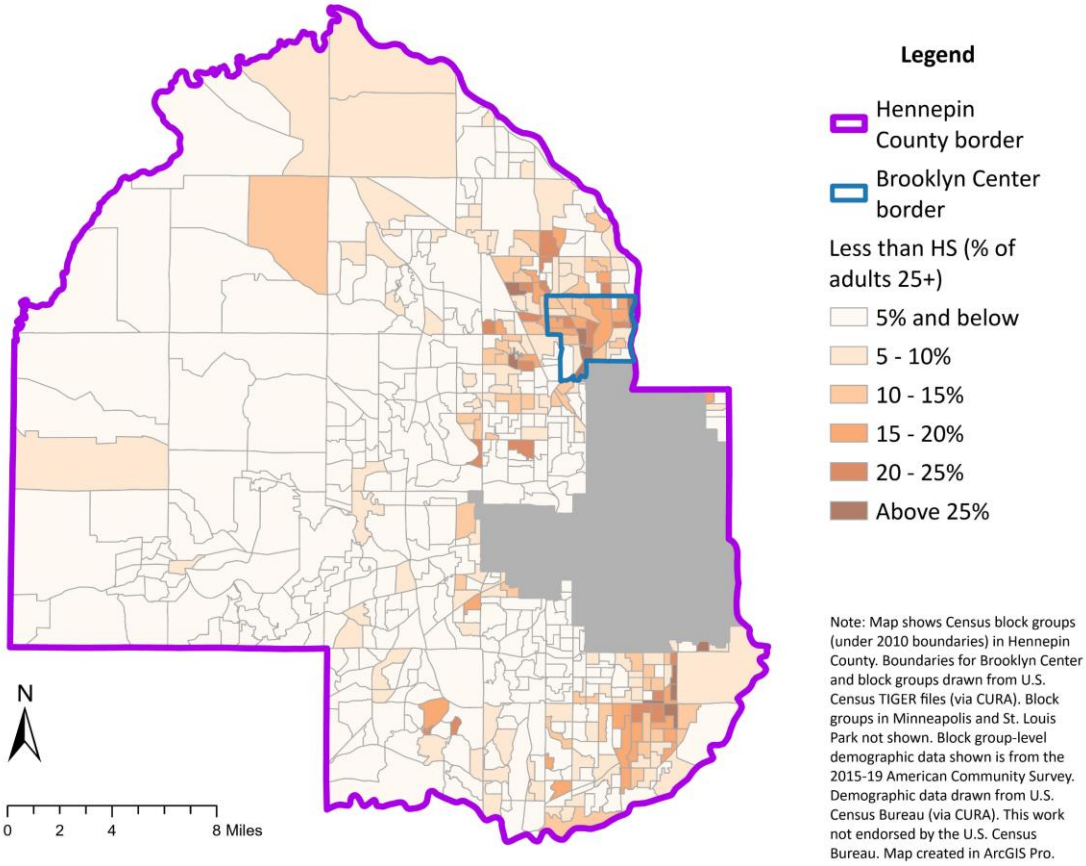


Fig. B-3. Highest educational attainment is bachelor's degree or higher as a share of the population 25+ in suburban Hennepin County (2015-19 ACS).

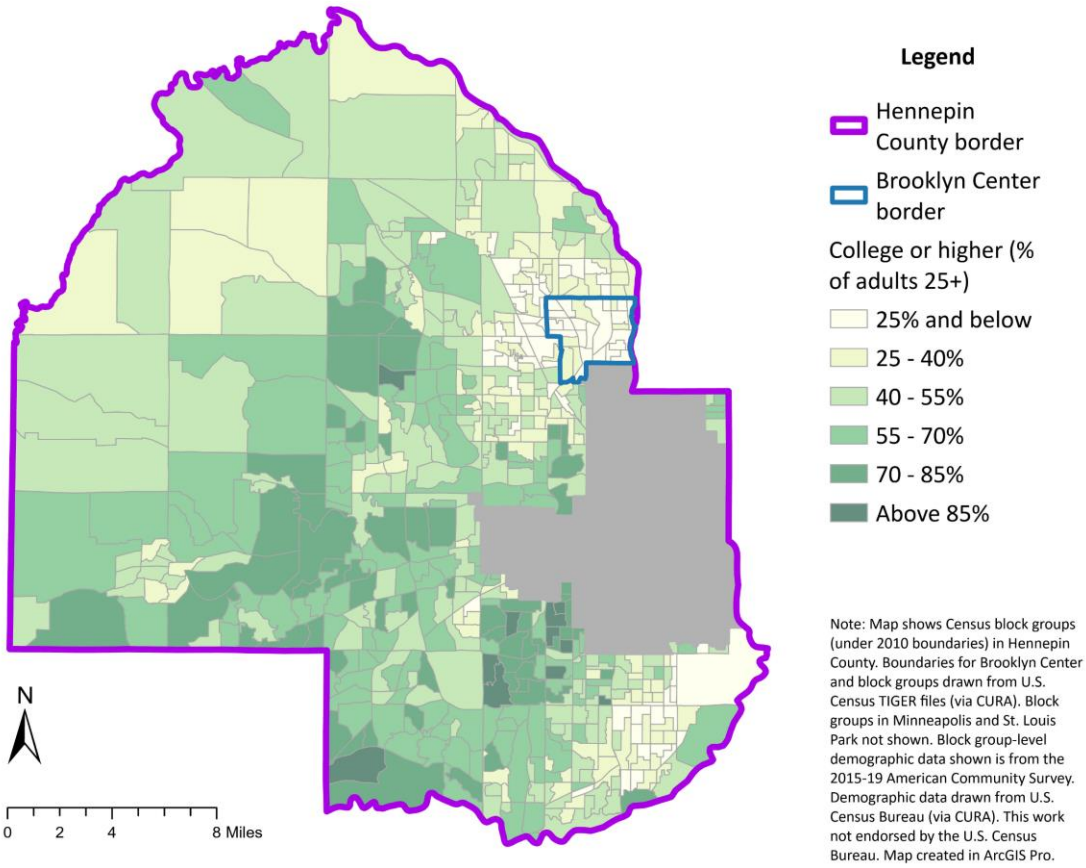


Fig. B-4. Hispanic, any race as a share of the population in suburban Hennepin County (2015-19 ACS).

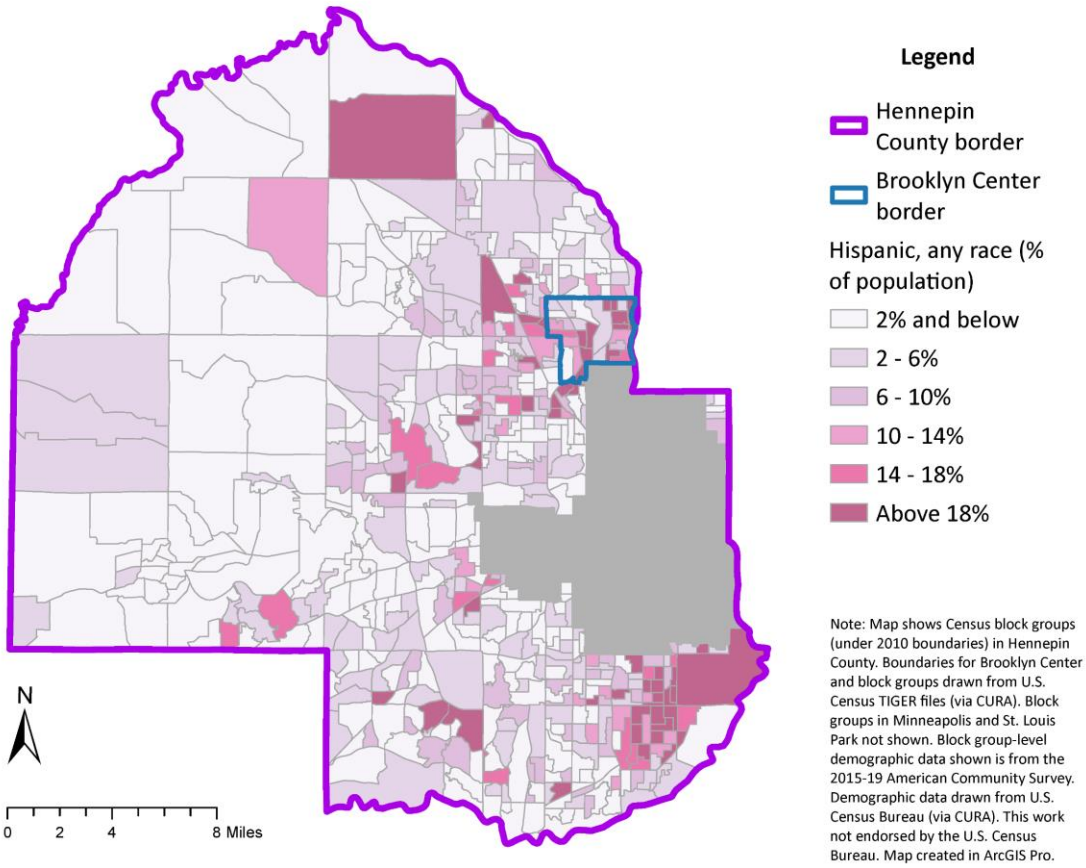


Fig. B-5. Black, non-Hispanic as a share of the population in suburban Hennepin County (2015-19 ACS).

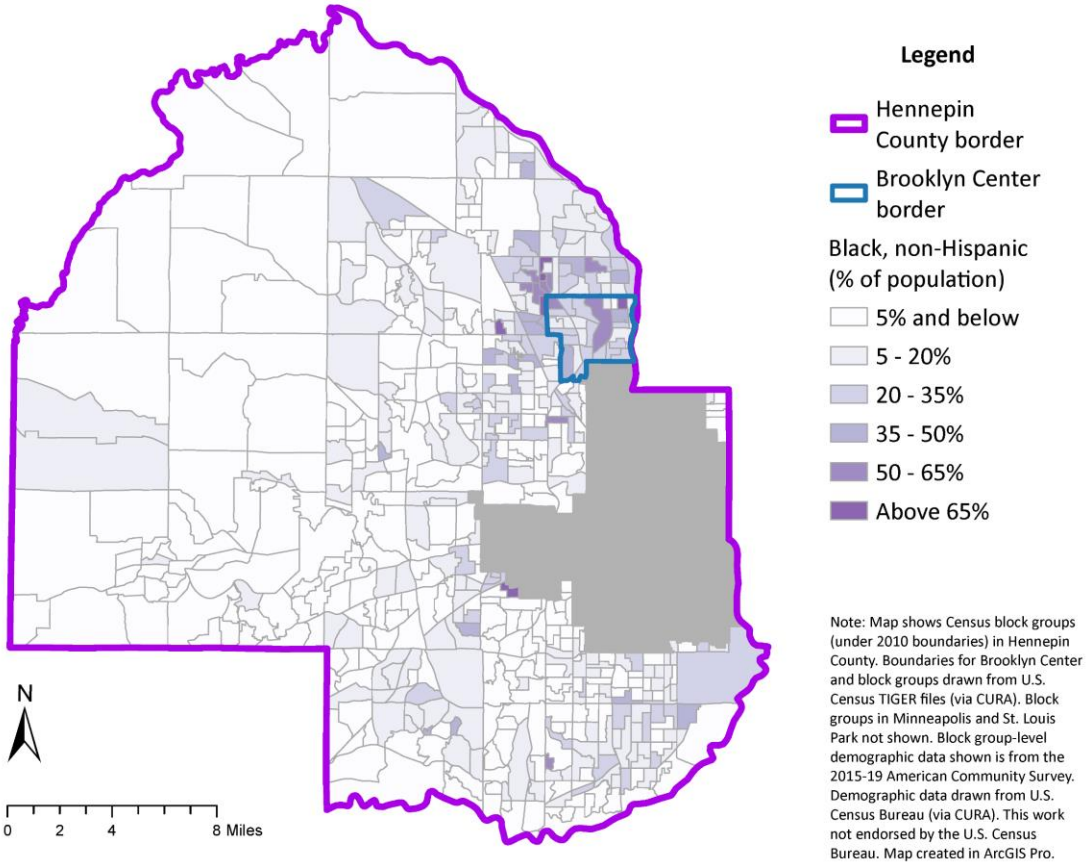


Fig. B-6. Median household income in suburban Hennepin County (2015-19 ACS).

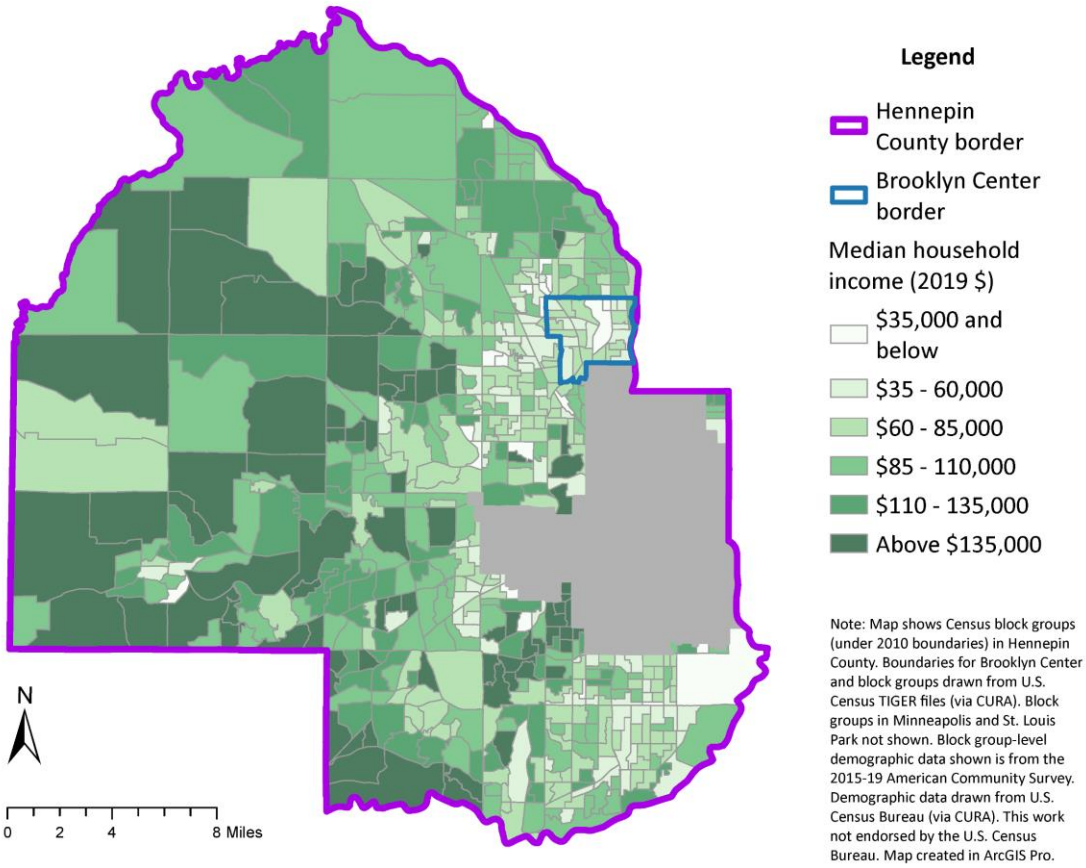


Table B-1. Block group-level descriptive statistics, various comparison groups.

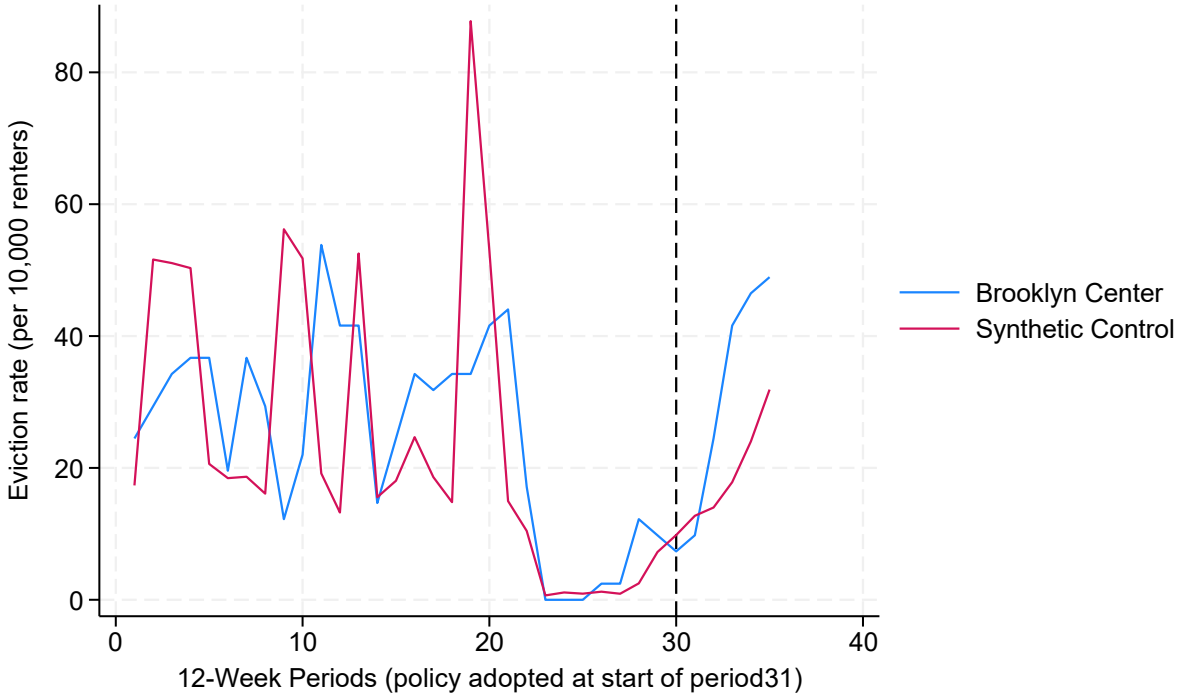
	Full suburban sample		Adjusted suburban sample: restricted to (a) exclude block groups with mobile home renters; (b) remove the top decile of block groups by group quarters pop. share (so the group quarters share is no more than 1.67%)							
Comparison group	Hennepin Co. (excl. Mpls, St. Louis Park)		Adj. suburban sample (other than BC)		Brooklyn Park		Matched group 1, cell estimator		Matched group 2, logistic model	
	Comp. 1	Brooklyn Center	Comp. 2	BC subset 2	Comp. 3	BC subset 3	Comp. 4	BC subset 4	Comp. 5	BC subset 5
Pre-COVID eviction data (2015-19)										
Evictions per filing (tract)	0.358	0.374	0.359	0.372	0.372	0.372	0.384	0.372	0.395	0.372
Dismissals per filing (tract)	0.144	0.116	0.145	0.118	0.136	0.118	0.118	0.120	0.107	0.120
Median age at eviction filing (tract)	39.1	37.6	39.2	37.8	35.8	37.8	34.3	37.9	34.3	37.9
Housing stock										
Renter-occup. units (% of occup. units)	0.252	0.371	0.240	0.371	0.267	0.371	0.476	0.373	0.348	0.372
Housing density (units per km^2, tract)	510	532	511	527	572	527	706	531	672	531
Publicly subsidized housing rate (tract)	0.094	0.124	0.092	0.121	0.137	0.121	0.114	0.123	0.164	0.123
Renter households										
Median gross rent	1,333	1,184	1,341	1,204	1,293	1,204	1,101	1,187	1,120	1,187
Pays 30-49% of income for housing	0.211	0.211	0.207	0.171	0.251	0.171	0.286	0.180	0.193	0.180
Pays 50% or more of inc. for housing	0.183	0.267	0.183	0.265	0.272	0.265	0.223	0.255	0.331	0.264
White, non-Hispanic (householder)	0.701	0.337	0.697	0.321	0.374	0.321	0.402	0.336	0.269	0.336
Hispanic, any race (householder)	0.062	0.175	0.060	0.176	0.048	0.176	0.171	0.165	0.157	0.170
Age 65+ (householder)	0.166	0.104	0.158	0.082	0.132	0.082	0.151	0.086	0.093	0.086
3+ people in household	0.371	0.516	0.381	0.572	0.448	0.572	0.397	0.574	0.520	0.563
Other demographic characteristics										
Median household income	98,133	61,805	100,190	62,040	77,509	62,040	58,986	60,548	62,924	62,040
Public assistance (share of households)	0.029	0.091	0.029	0.096	0.082	0.096	0.080	0.094	0.130	0.101
Born outside U.S. (householder, tract)	0.126	0.237	0.128	0.231	0.233	0.231	0.201	0.230	0.218	0.230
Single woman (householder)	0.137	0.273	0.137	0.261	0.229	0.261	0.221	0.256	0.230	0.256
Less than HS or equiv. (adults 25+)	0.050	0.153	0.049	0.157	0.106	0.157	0.143	0.149	0.161	0.157
Bachelor's or higher (adults 25+)	0.490	0.200	0.495	0.196	0.284	0.196	0.277	0.198	0.168	0.194
Block group count	528	26	464	22	50	22	73	21	410	21
Weights applied							Inverse prob. weights to approximate BC		Inverse prob. weights to approximate BC	

Note: Suburban sample includes all Hennepin County Census Block Groups (under 2010 boundaries), excluding Minneapolis and St. Louis Park. Demographic data provided reflect renter householders by block group, unless stated otherwise. Demographic characteristics are reported for the household head. Eviction filing and judgment rates reported as average of weekly rate per 10,000 renter-occupied housing units in the relevant block groups. Age and household income calculated in two step process: median calculated within tracts; then tract means calculated across all block groups by category. Median days to judgment is calculated using the number of days between an eviction filing and a judgment of eviction (excluding cases with other outcomes). Matched comparison group 1 identified via cell estimator, with weights to approximate ATT; block groups excluded if not in common support. Matched group 1 assigned propensity scores by cells constructed using *(a) deciles for median household income (by tract); (b) deciles for adults 25+ with less than HS education (by block group); and (c) deciles for adults 25+ whose highest education level was a bachelor's degree (by block group)*. Matched comparison group 2 identified via *psmatch2*, using a logistic regression to form propensity scores; block groups excluded if not in common support. For matched comp. group 2, the covariates used to form propensity scores were: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. Data: MN Judicial Branch via CURA; ACS 2015-19 5-Year Estimates; U.S. Census Bureau Data API (this work not endorsed by the Census Bureau); IPUMS NHGIS (Manson et al., 2022); HUD Office of Policy Development and Research (U.S. Department of Housing and Urban Development, 2023).

Appendix C: SC models, eviction rates

Fig. C-1 below is an initial synthetic control model to estimate Brooklyn Center eviction rates. The only covariate used to form the synthetic control in this model is the eviction rate from periods 1-22.

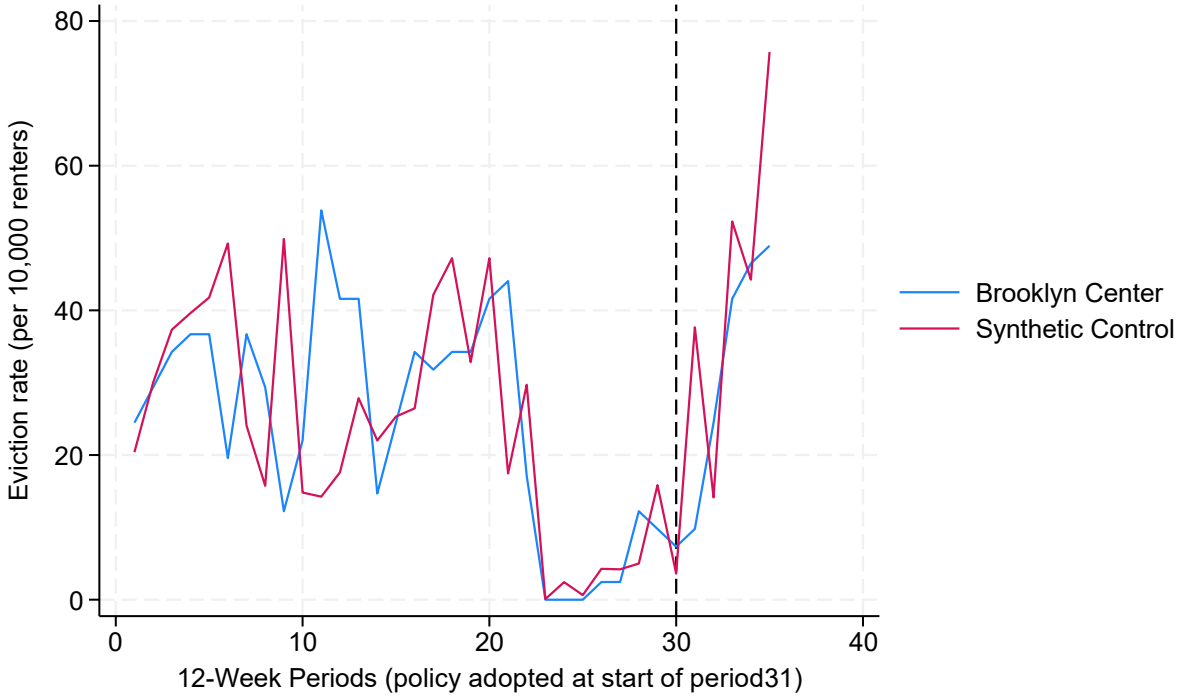
Fig. C-1. Eviction rates, Brooklyn Center and Synthetic Control (only eviction rates).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities are assigned weights relatively evenly, with a weight of 0.194 for St. Bonifacius. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 1-22. Eviction rate calculated using ACS 2015-19 data on renter-occupied housing units by city, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. C-2 below is a second synthetic control model focused on eviction rates in Brooklyn Center. This model includes covarates related to economic and educational characteristics by city. Compared to **Fig. C-1** above, this figure adds these covariates: the natural log of median household income, the fraction of renter households that paid 30-49% of income for housing, the fraction of renter households that paid 50% or more of income for housing, the fraction of renter householders with less than a high school education, and the fraction of renter householders with a bachelor's degree or higher.

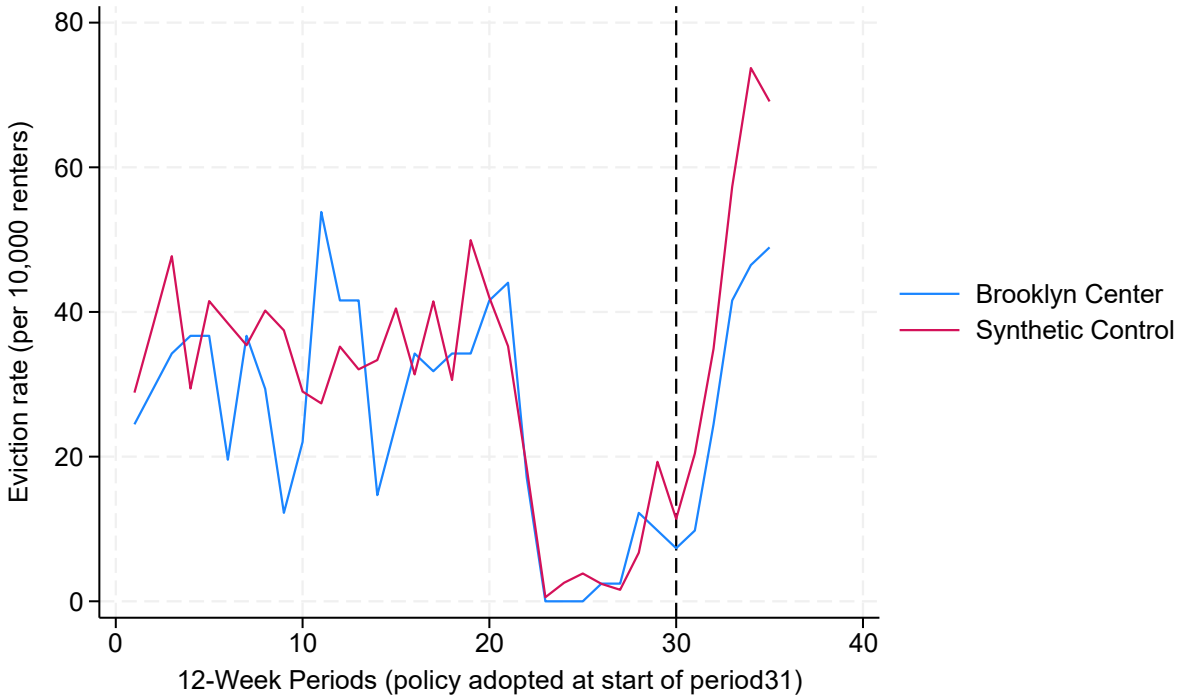
Fig. C-2. Eviction rates, Brooklyn Center and Synthetic Control (adding economic and education covariates).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Robbinsdale, Medina, Fort Snelling Unorganized Territory, Brooklyn Park, Richfield, and Orono. This model assigned weights of 0.412 to Robbinsdale, 0.234 to Medina, 0.223 to Fort Snelling Unorganized Territory, and weights below 0.1 to the other cities. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. C-3 below is a third synthetic control model focused on eviction rates in Brooklyn Center. This model includes covarates related to race, ethnicity, and immigrant populations by city. Compared to **Fig. C-2** above, this figure adds these covariates: the fraction of renter householders who are white non-Hispanic, the fraction of renter householders who are Hispanic (any race), and the fraction of population that was born outside the U.S. **Fig. 5** in the main text is similar to this model, but also adds covariates related to household characteristics including two variables related to the age of the householder, the fraction of family households by city, and the fraction of renter households with 3 or more people.

Fig. C-3. Eviction rates, Brooklyn Center and Synthetic Control (adding race, ethnicity, and immigration covariates).

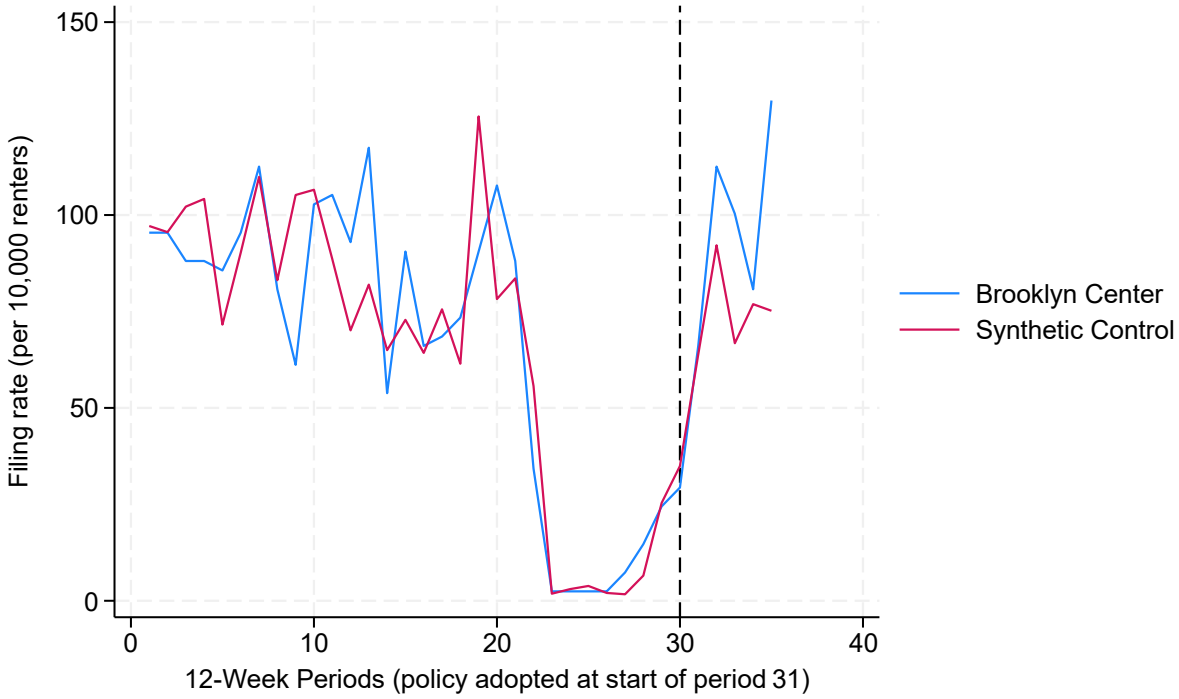


Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, Fort Snelling Unorganized Territory, and New Hope. This model assigned weights of 0.462 to Richfield, 0.396 to Brooklyn Park, 0.123 to Fort Snelling Unorganized Territory, an 0.019 to New Hope. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Appendix D: SC models, eviction filing rates

Fig. D-1 below is an initial synthetic control model to estimate Brooklyn Center eviction filing rates. The only covariate used to form the synthetic control in this model is the eviction rate from periods 1-22.

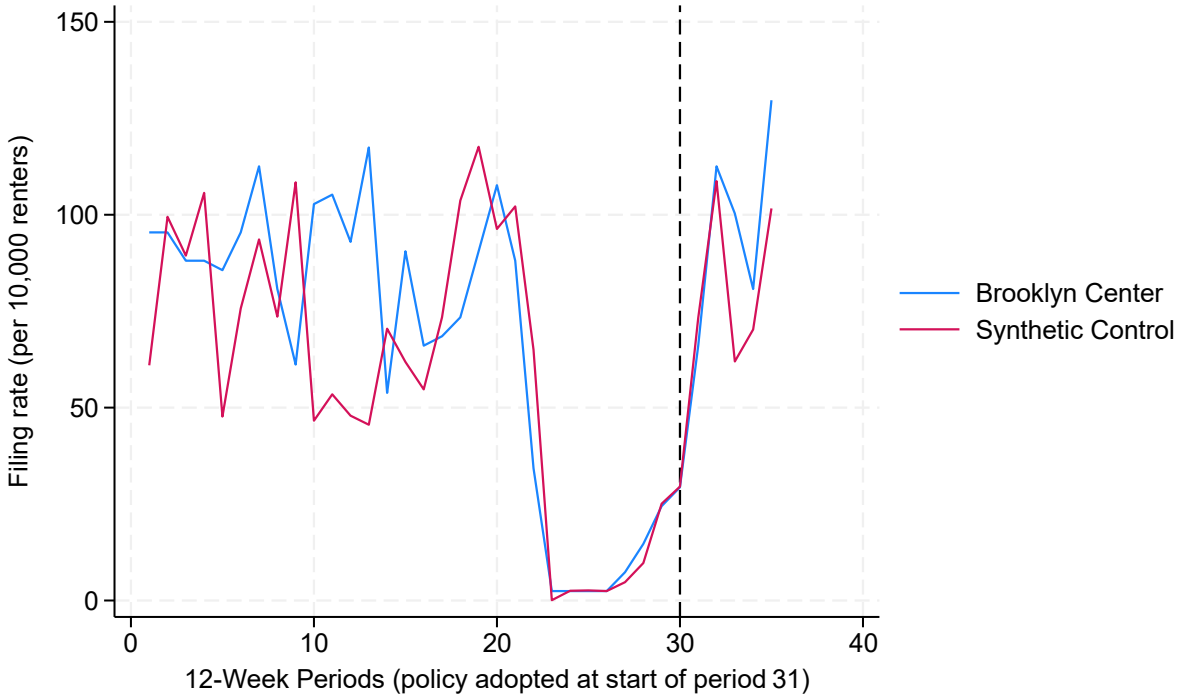
Fig. D-1. Eviction filing rates, Brooklyn Center and Synthetic Control.



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities are assigned weights relatively evenly, with a weight of 0.256 for Brooklyn Park. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 1-22. Eviction filing rate calculated using ACS 2015-19 data on renter-occupied housing units by city, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. D-2 below is a second synthetic control model focused on eviction filing rates in Brooklyn Center. This model includes covarates related to economic and educational characteristics by city. Compared to **Fig. D-1** above, this figure adds these covariates: the natural log of median household income, the fraction of renter households that paid 30-49% of income for housing, the fraction of renter households that paid 50% or more of income for housing, the fraction of renter householders with less than a high school education, and the fraction of renter householders with a bachelor's degree or higher.

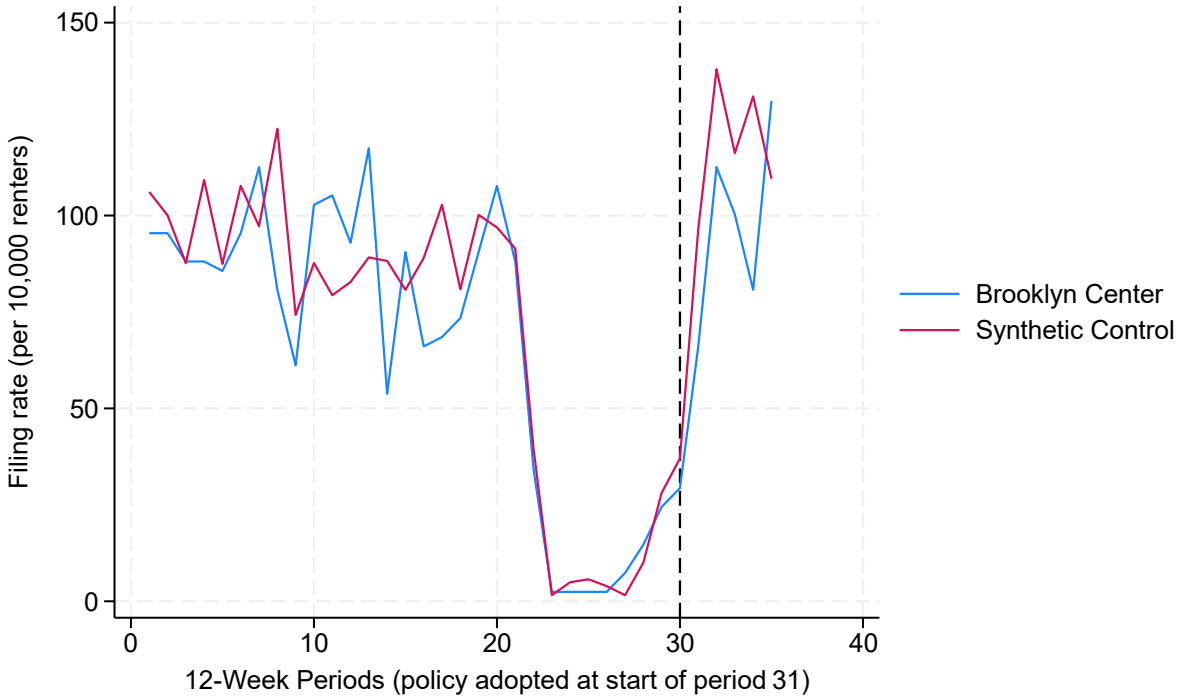
Fig. D-2. Eviction filing rates, Brooklyn Center and Synthetic Control (adding economic and education covariates).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Robbinsdale, Fort Snelling Unorganized Territory, Medina, Orono, Brooklyn Park, and Richfield. This model assigned weights of 0.491 to Robbinsdale, 0.232 to Fort Snelling Unorganized Territory, 0.212 to Medina, and weights below 0.1 to the other cities. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. D-3 below is a third synthetic control model focused on eviction filing rates in Brooklyn Center. This model includes covarates related to race, ethnicity, and immigrant populations by city. Compared to **Fig. D-2** above, this figure adds these covariates: the fraction of renter householders who are white non-Hispanic, the fraction of renter householders who are Hispanic (any race), and the fraction of population that was born outside the U.S. **Fig. 7** in the main text is similar to this model, but also adds covariates related to household characteristics including two variables related to the age of the householder, the fraction of family households by city, and the fraction of renter households with 3 or more people.

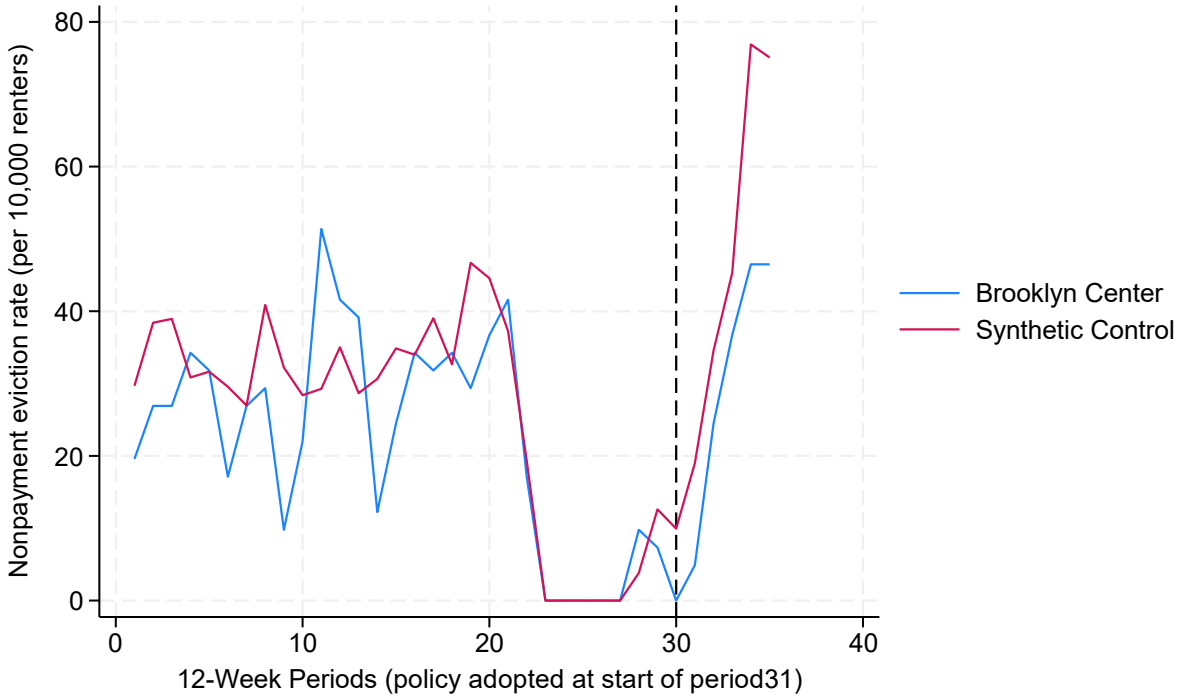
Fig. D-3. Eviction filing rates, Brooklyn Center and Synthetic Control (adding race, ethnicity, and immigration covariates).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, Fort Snelling Unorganized Territory, and Hopkins. This model assigned weights of 0.531 to Richfield, 0.409 to Brooklyn Park, 0.030 to Fort Snelling Unorganized Territory, and 0.030 to Hopkins. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

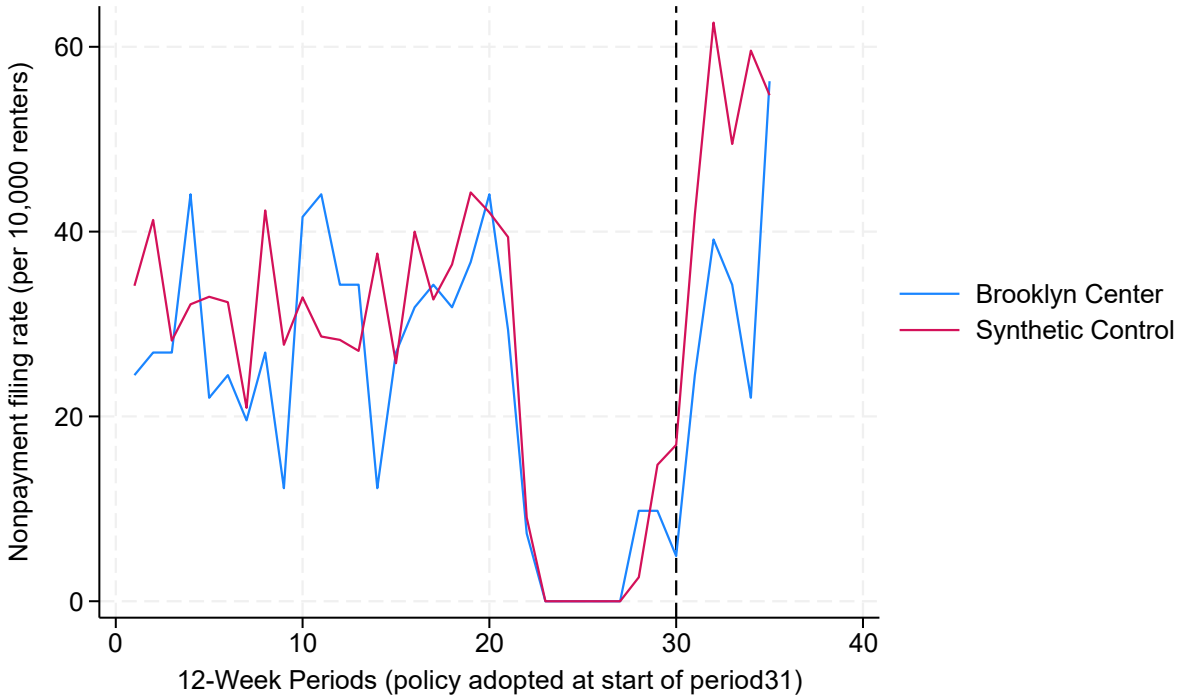
Appendix E: SC models, nonpayment

Fig. E-1. Eviction rates for nonpayment, Brooklyn Center and Synthetic Control.



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate (nonpayment cases) trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and New Hope. This model assigned weights of 0.531 to Richfield, 0.421 to Brooklyn Park, and 0.048 to New Hope. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in nonpayment cases in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

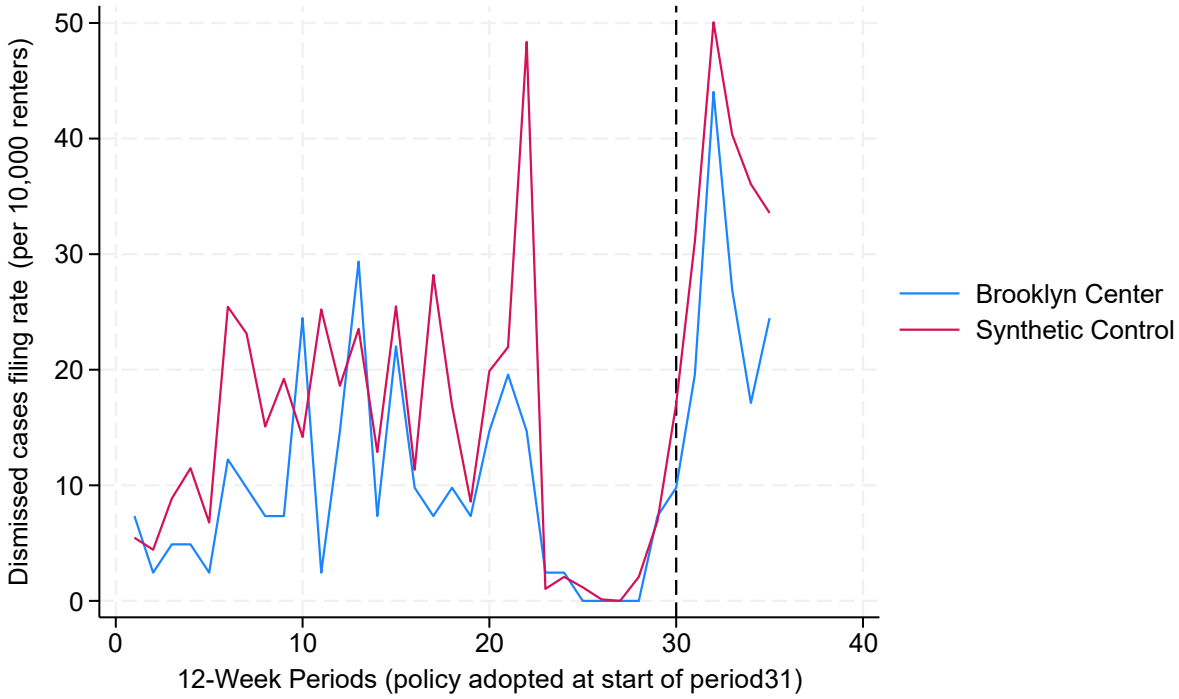
Fig. E-2. Eviction filing rates for nonpayment of rent, Brooklyn Center and Synthetic Control.



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate (nonpayment cases) trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, Brooklyn Park, and Medina. This model assigned weights of 0.578 to Richfield, 0.401 to Brooklyn Park, and 0.021 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction filing rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in nonpayment cases in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

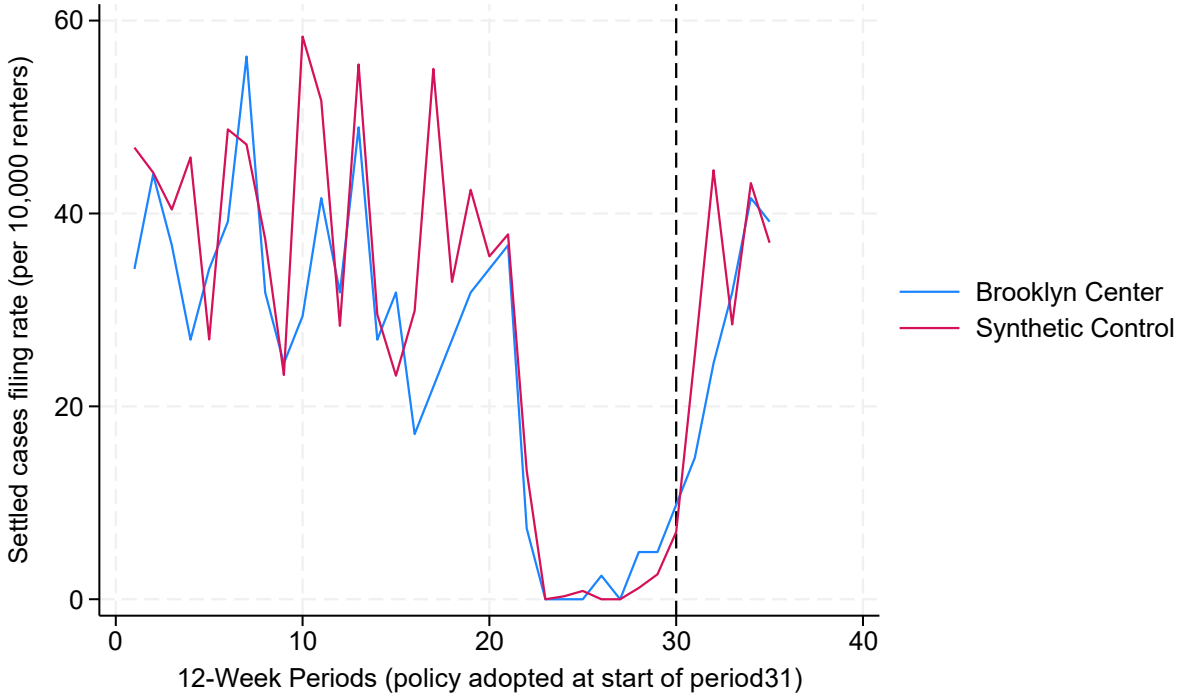
Appendix F: SC models, eviction filing rates in cases that were dismissed, settled, or resulted in tenant redemption

Fig. F-1. Eviction filing rates in dismissed cases, Brooklyn Center and Synthetic Control.



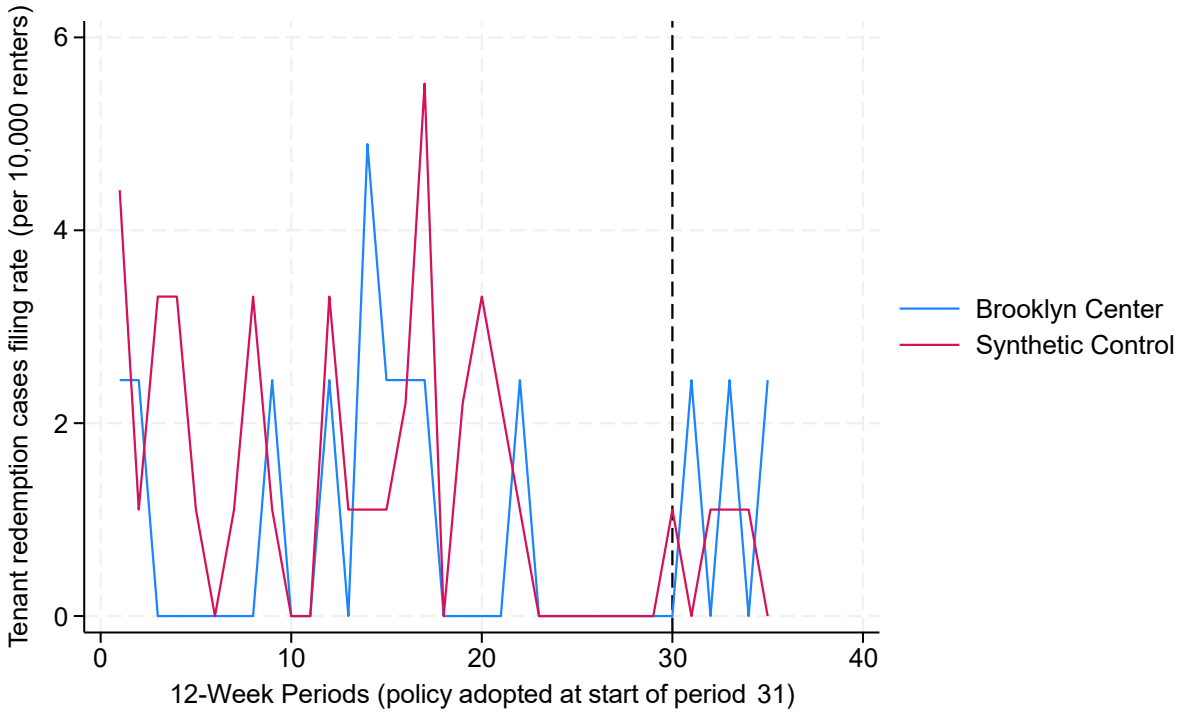
Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate (dismissed cases) trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Brooklyn Park, St. Bonifacius, Richfield, and Minnetrista. This model assigned weights of 0.802 to Brooklyn Park, 0.086 to St. Bonifacius, 0.081 to Richfield, and 0.031 to Minnetrista. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction filing rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in dismissed cases in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. F-2. Eviction filing rates in settled cases, Brooklyn Center and Synthetic Control.



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate (settled cases) trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Brooklyn Park, Richfield, St. Bonifacius, and Medina. This model assigned weights of 0.665 to Brooklyn Park, 0.187 to Richfield, 0.125 to St. Bonifacius, and 0.023 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction filing rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in settled cases in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. F-3. Eviction filing rates in cases resulting in tenant redemption, Brooklyn Center and Synthetic Control.



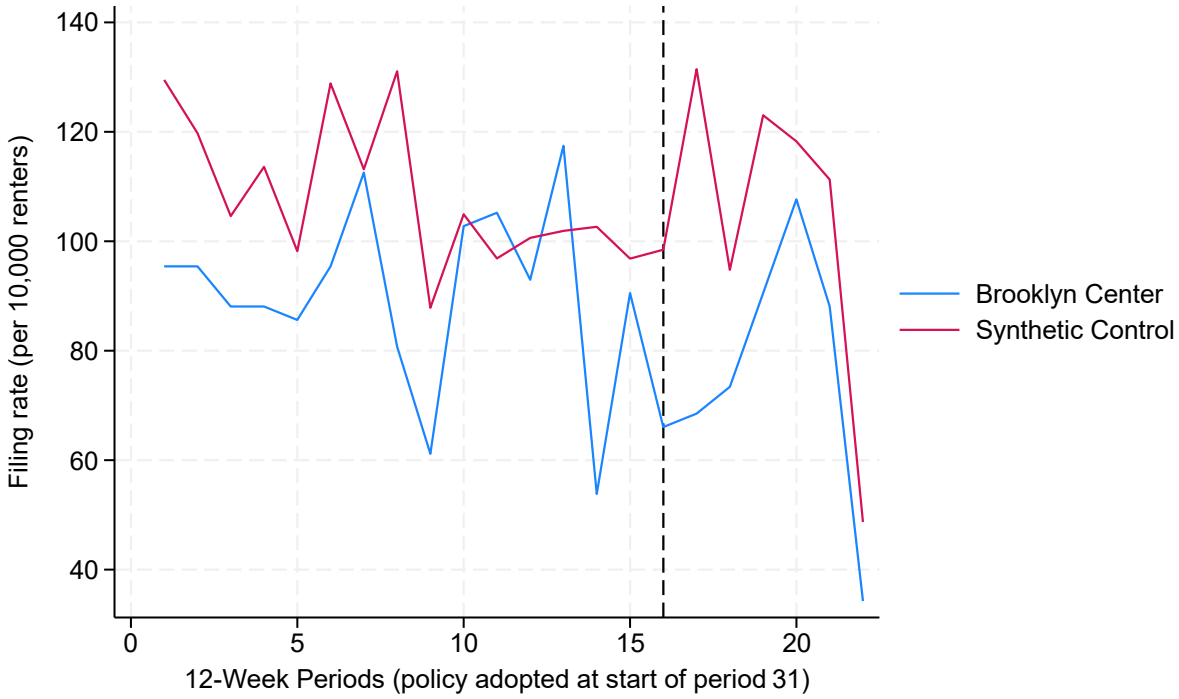
Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate (cases resulting in tenant redemption) trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Brooklyn Park, St. Bonifacius, and Medina. This model assigned weights of 0.852 to Brooklyn Park, 0.096 to St. Bonifacius, and 0.052 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction filing rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in cases resulting in tenant redemption in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Appendix G: Placebo tests for SC, fake treatment date

Fig. G-1. Placebo test with treatment date in period 17: eviction rates, Brooklyn Center and Synthetic Control (sample restricted to periods 1-22).

Note: Figure shows a placebo test, reporting a synthetic control model for Brooklyn Center eviction rate trends after a fake treatment date in period 17. All periods shown here are from before March 2020. The donor pool cities assigned weights other than 0 are Brooklyn Park, Richfield, and Medina. This model assigned weights of 0.547 to Brooklyn Park, 0.412 to Richfield, and 0.041 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 9-16, and this set of covariates by city in periods 1-16: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

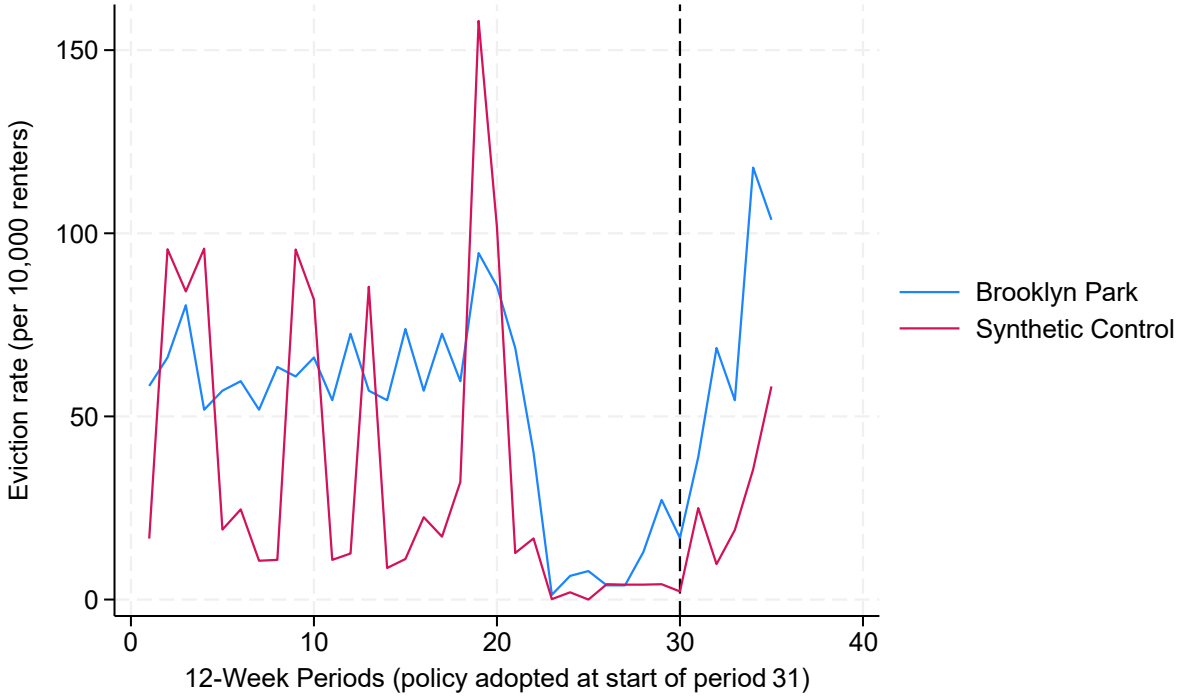
Fig. G-2. Placebo test with treatment date in period 17: eviction filing rates, Brooklyn Center and Synthetic Control (sample restricted to periods 1-22).



Note: Figure shows a placebo test, reporting a synthetic control model for Brooklyn Center eviction filing rate trends after a fake treatment date in period 17. All periods shown here are from before March 2020. The donor pool cities assigned weights other than 0 are Brooklyn Park, Richfield, and Eden Prairie. This model assigned weights of 0.564 to Brooklyn Park, 0.303 to Richfield, and 0.133 to Eden Prairie. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 9-16, and this set of covariates by city in periods 1-16: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

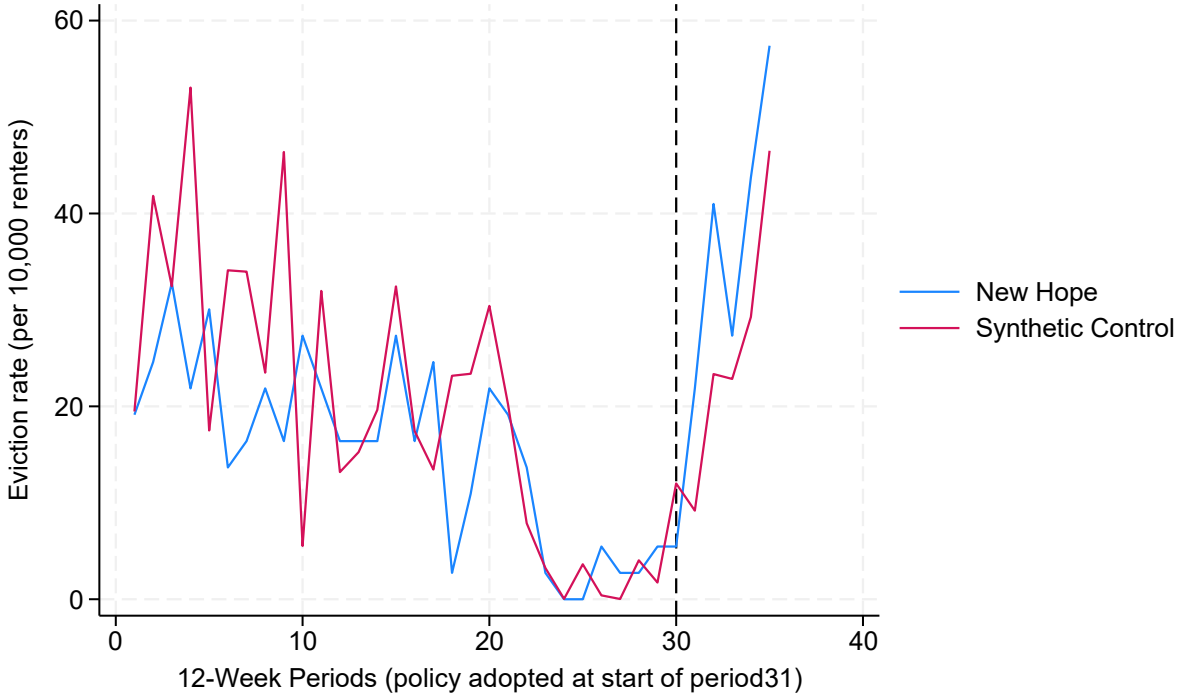
Appendix H: Placebo tests for SC, treated city as Brooklyn Park, New Hope, or Richfield

Fig. H-1: Placebo test: eviction rates, Brooklyn Park and Synthetic Control.



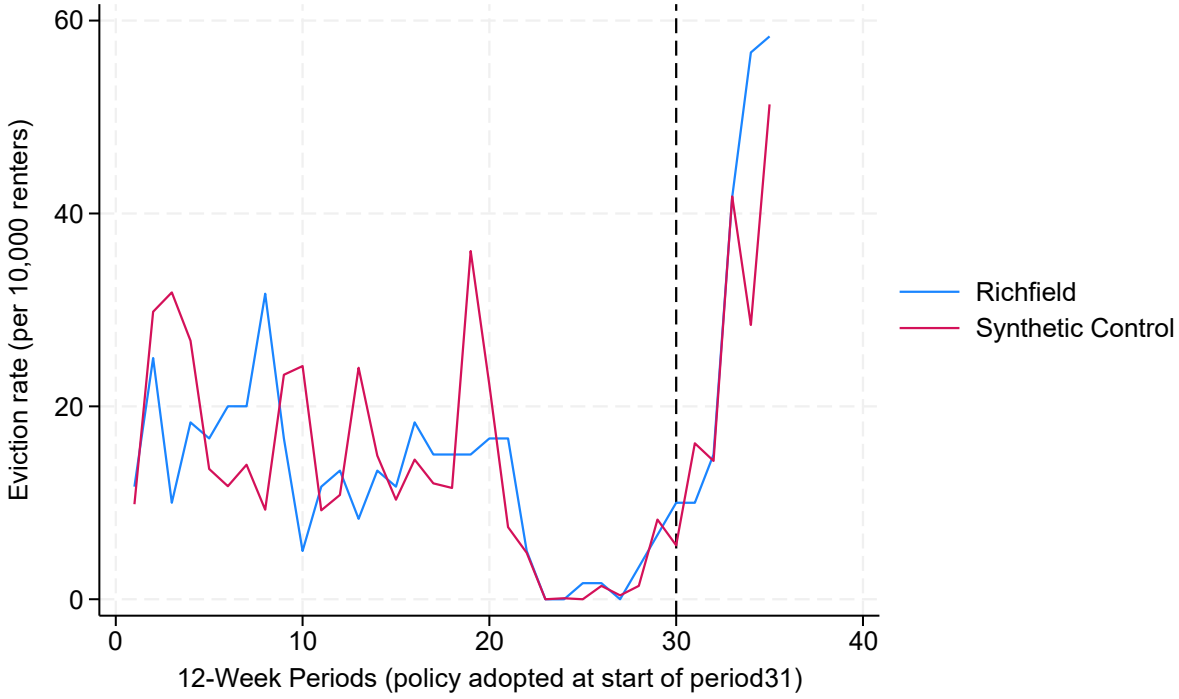
Note: Figure shows a placebo test using Brooklyn Park as the treated city. This is a synthetic control model that approximates Brooklyn Park eviction rate trends after February 28, 2022. The donor pool cities assigned weights other than 0 are St. Bonifacius, Robbinsdale, Medina, and New Hope. This model assigned weights of 0.425 to St. Bonifacius, 0.417 to Robbinsdale, 0.115 to Medina, and 0.043 to New Hope. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Fig. H-2. Placebo test: eviction rates, New Hope and Synthetic Control.



Note: Figure shows a placebo test using New Hope as the treated city. This is a synthetic control model that approximates New Hope eviction rate trends after February 28, 2022. The donor pool cities assigned weights other than 0 are Crystal, Richfield, Hopkins, Rogers, Brooklyn Park, and Deephaven. The model assigned weights of 0.750 to Crystal, 0.203 to Richfield, and weights below 0.1 to the other cities. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

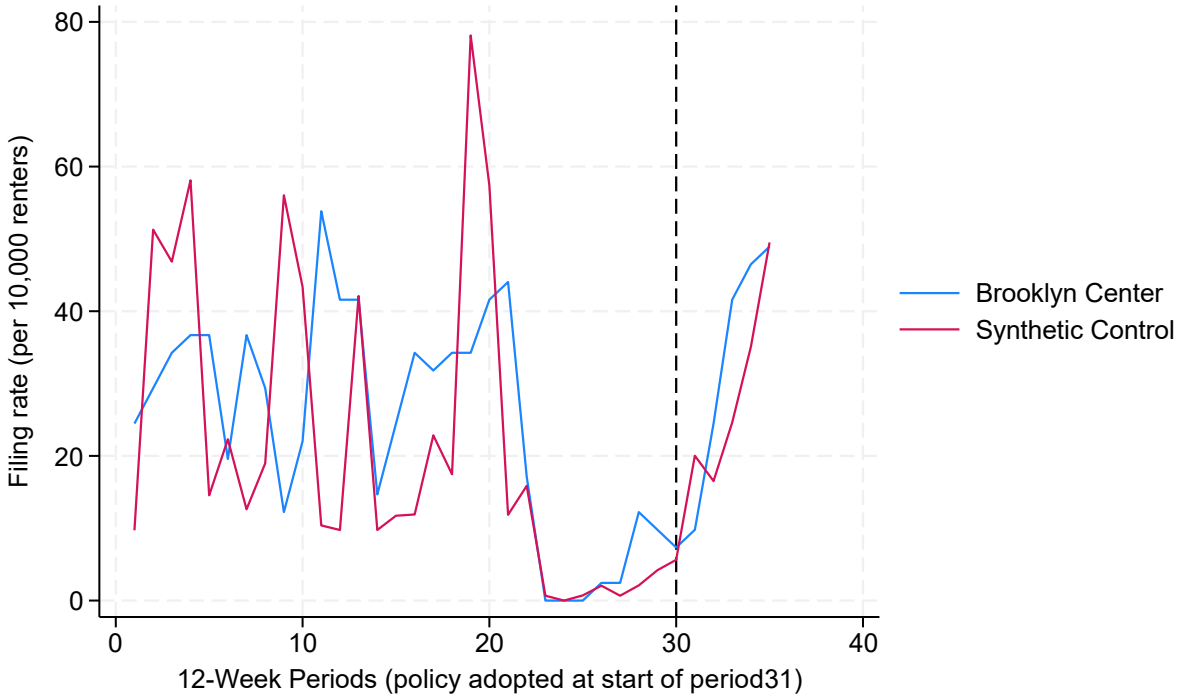
Fig. H-3. Placebo test: eviction rates, Richfield and Synthetic Control.



Note: Figure shows a placebo test using Richfield as the treated city. This is a synthetic control model that approximates Richfield eviction rate trends after February 28, 2022. The donor pool cities assigned weights other than 0 are Hopkins, Eden Prairie, St. Bonifacius, Maple Plain, and Robbinsdale. This model assigned weights of 0.681 to Hopkins, 0.130 to Eden Prairie, and weights below 0.1 to the other cities. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

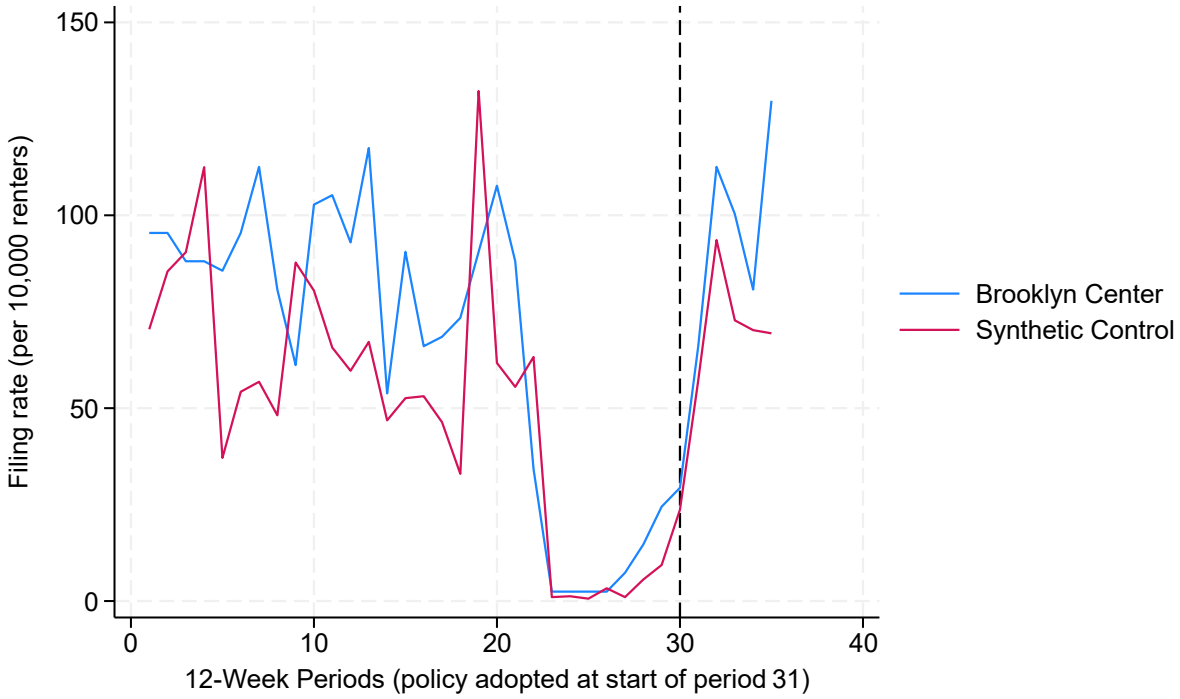
Appendix I: Robustness checks for SC, Brooklyn Park excluded from donor pool

Fig. I-1. Eviction rates, Brooklyn Center and Synthetic Control (Brooklyn Park not included in donor pool).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are Richfield, New Hope, St. Bonifacius, and Medina. This model assigned weights of 0.429 to Richfield, 0.246 to New Hope, 0.207 to St. Bonifacius, and 0.117 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

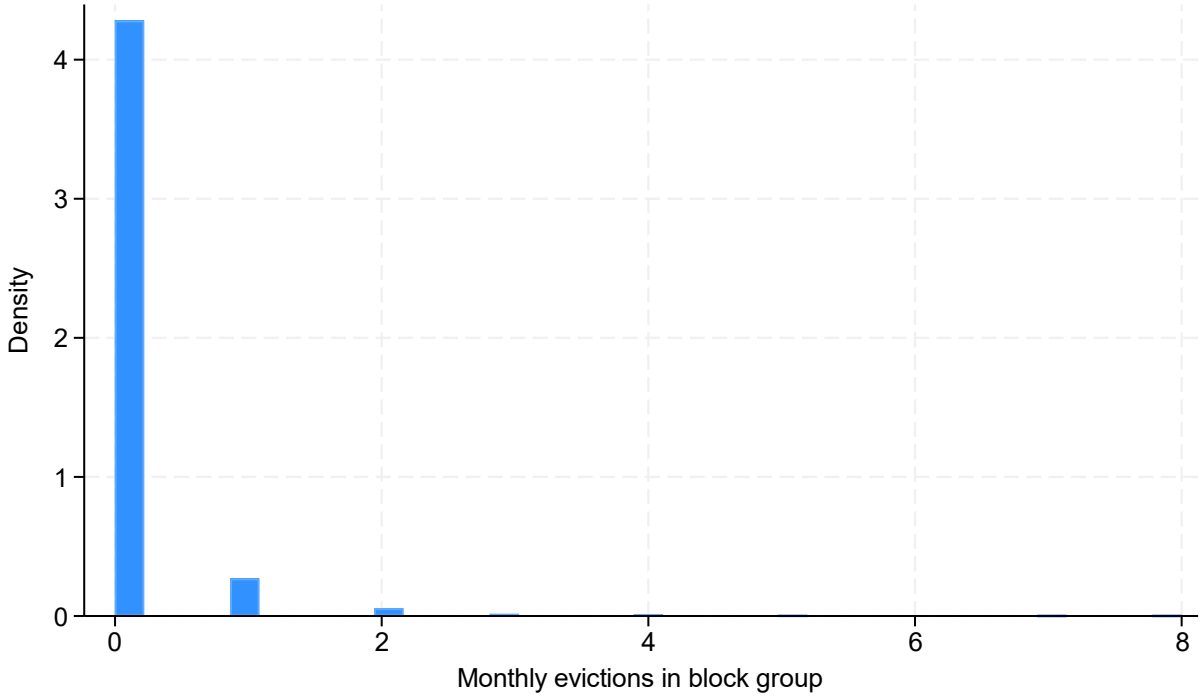
Fig. I-2. Eviction filing rates, Brooklyn Center and Synthetic Control (Brooklyn Park not included in donor pool).



Note: Figure shows a synthetic control model that approximates Brooklyn Center eviction filing rate trends after the adoption of the Tenant Protection ordinance on February 28, 2022. The donor pool cities assigned weights other than 0 are New Hope, Richfield, St. Bonifacius, and Medina. This model assigned weights of 0.377 to New Hope, 0.375 to Richfield, 0.126 to St. Bonifacius, and 0.122 to Medina. 12-week periods defined relative to the ordinance adoption date. Period 31 starts on February 28, 2022. Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The first and last periods are excluded, to ensure all periods represent 12 full weeks. Eviction rate calculated per 10,000 renter-occupied housing units in city. This synthetic control model was formed using eviction filing rates in periods 13-22, and this set of covariates by city in periods 1-22: *natural log of median household income, fraction of renter households that paid 30-49% of income for housing, fraction of renter households that paid 50% or more of income for housing, fraction of renter householders with less than a high school education, fraction of renter householders with a bachelor's degree or higher, fraction of renter householders who are white non-Hispanic, fraction of renter householders who are Hispanic (any race), fraction of population that was born outside the U.S., fraction of renter householders ages 34 and under, fraction of renter householders ages 65+, fraction of renter households that are families, fraction of renter households with 3 or more people*. All covariates formed using ACS 2015-19 data, accessed via Social Explorer. Figure created using the *synth* Stata package developed by Abadie et al. (2010), as well as the *synth_runner* package developed by Galiani and Quistorff (2017). This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Hennepin County subdivision using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Appendix J: Histogram of evictions by block group-month

Fig. J-1. Histogram of evictions by block group-month from mid-October 2021 to mid-October 2022.

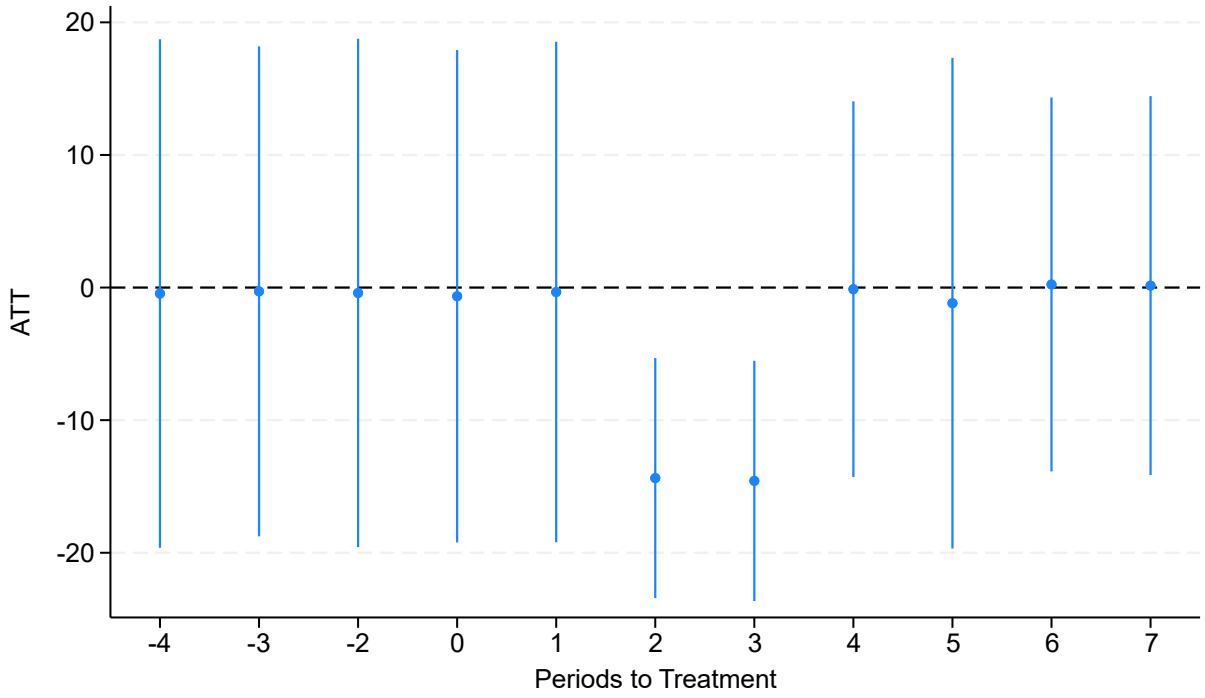


Note: Eviction data drawn from Minnesota Judicial Branch via CURA for the period from January 2015 to early July 2023. The histogram shows evictions by block group-month in the last four 30-day periods before 2/28/2022, and the first eight 30-day periods since that date. This analysis focuses on household-level evictions. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by Census block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau.

Appendix K: DiD event studies, negative binomial regression

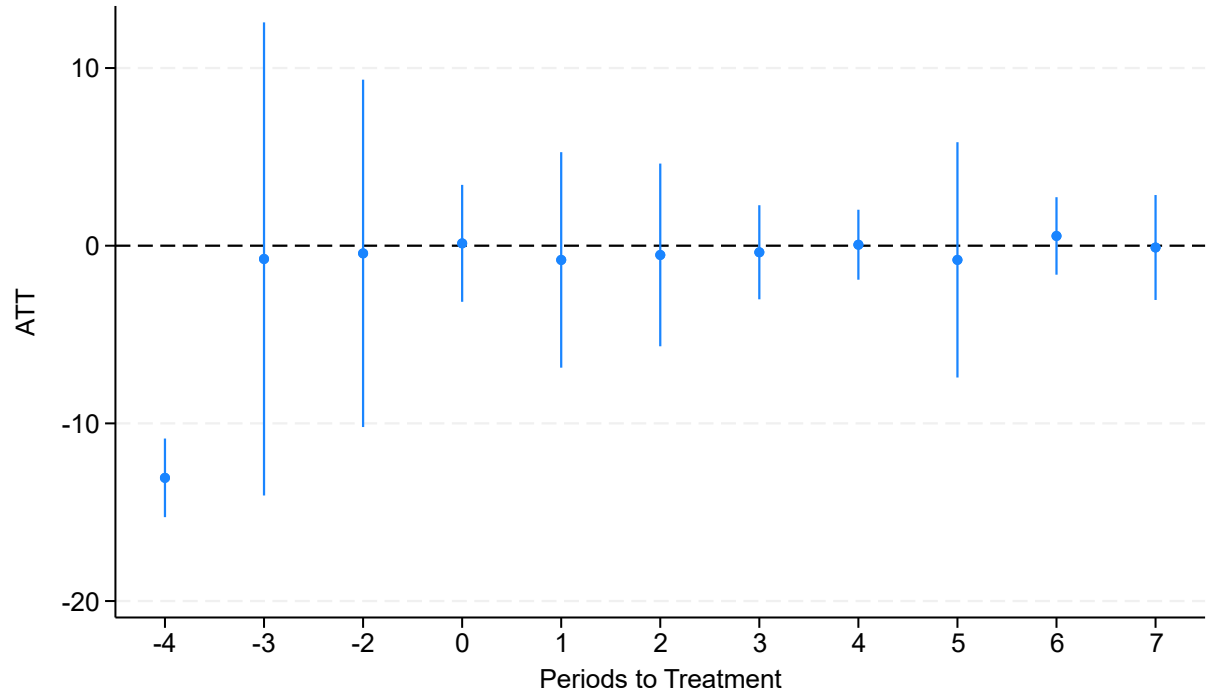
To estimate treatment effects on eviction counts and eviction filing counts, I created event study plots via negative binomial regressions with fixed effects. The model for eviction counts, reported in **Fig. K-1** below, shows that block group-level eviction counts in Brooklyn Center decreased in the first two 30-day periods after policy adoption relative to the comparison group. The model for eviction filing counts, reported in **Fig. K-2** below, shows violations of pre-trends. Neither model adjusts for pre-treatment covariates.

Fig. K-1. Negative binomial event study, eviction counts in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample.



Note: Figure shows difference-in-differences event study, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction counts calculated within block groups. Figure created using the *xtnbreg* and *coefplot* Stata packages, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by filing date and block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 1,000 bootstrap replications; bars show 95% confidence intervals.

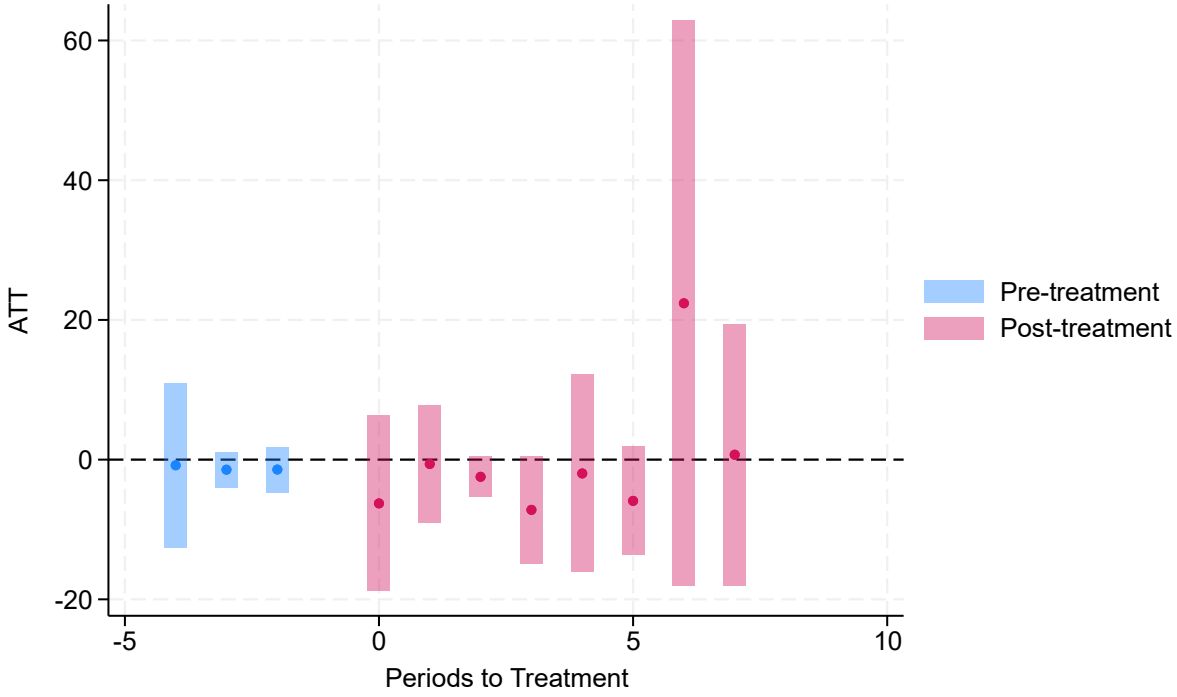
Fig. K-2. Negative binomial event study, eviction filing counts in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample.



Note: Figure shows difference-in-differences event study, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction filing counts calculated within block groups. Figure created using the *xtnbreg* and *coefplot* Stata packages, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level eviction filings, aggregated into a panel of eviction filings by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 1,000 bootstrap replications; bars show 95% confidence intervals.

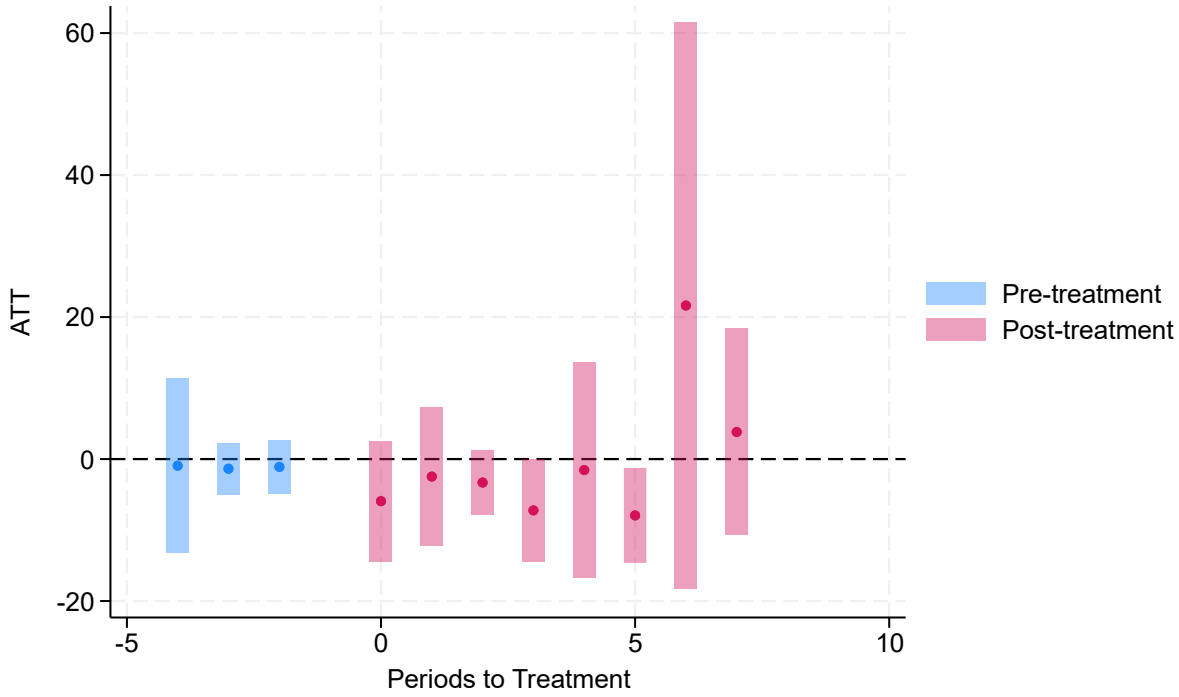
Appendix L: DiD event studies, nonpayment

Fig. L-1. Event study, rates of evictions for nonpayment in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample, first specification (more granular controls).



Note: Figure shows difference-in-differences event study focusing on eviction rates for nonpayment, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

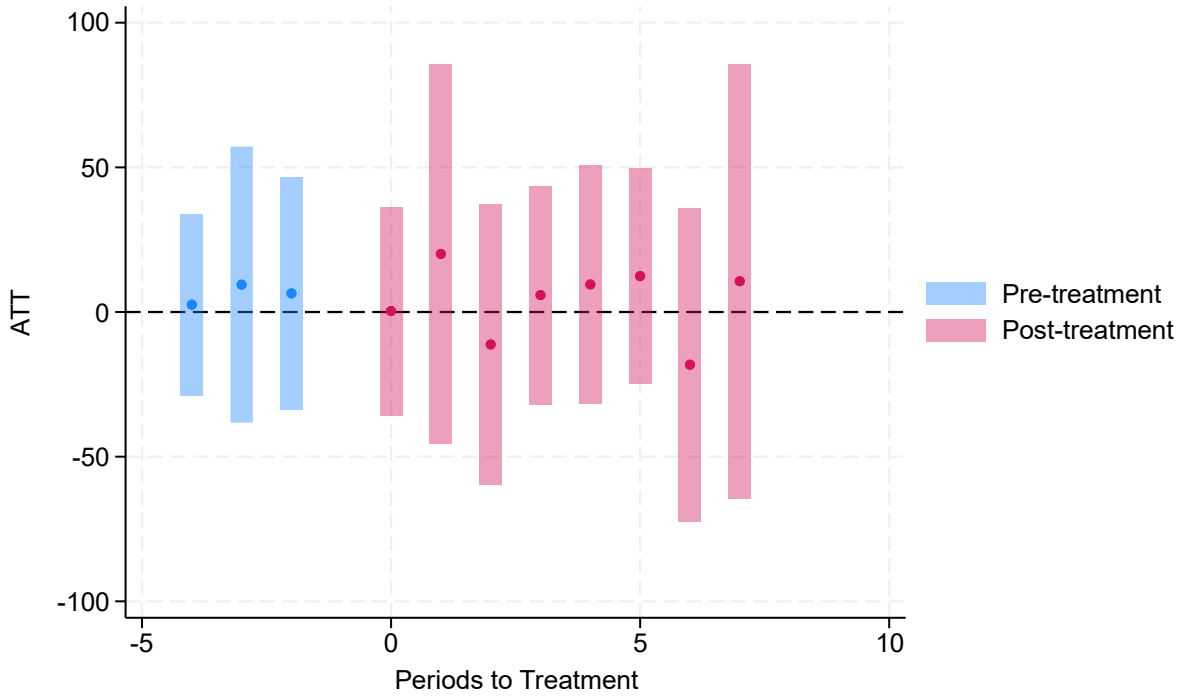
Fig. L-2. Event study, rates of eviction for nonpayment in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample, second specification (fewer controls).



Note: Figure shows difference-in-differences event study focusing on eviction rates for nonpayment, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renters who pay 30% of income for housing*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Appendix M: DiD event study, expungement rates

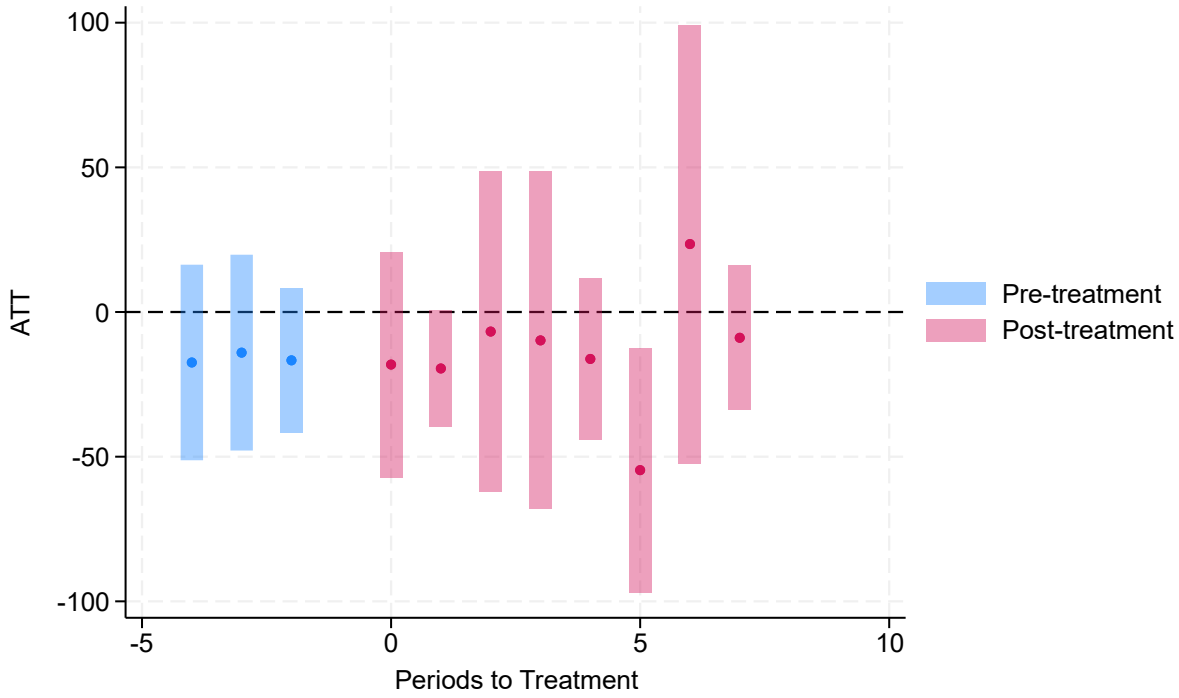
Fig. M-1. Event study, expungement rates (this is an indirect check, calculated as the difference in rates of eviction filings between HOME Line and state court data).



Note: Figure shows difference-in-differences event study, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. Outcome variable is the difference in the rates of eviction filings per 10,000 renter-occupied housing units, between HOME Line data on eviction filings and state court system data on eviction filings. Difference in eviction filing rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). Eviction filing data drawn from Minnesota Judicial Branch via CURA and HOME Line. For Judicial Branch data, duplicate records of evictions filed on the same date with the same address or case number removed. Minnesota Judicial Branch data geocoded with ggmap and Google Maps API, and data aggregated by block group using US Census Bureau Data API. HOME Line data geocoded and aggregated by block group using ArcGIS Pro. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Appendix N: Robustness check for DiD, filing data drawn from alternate data source

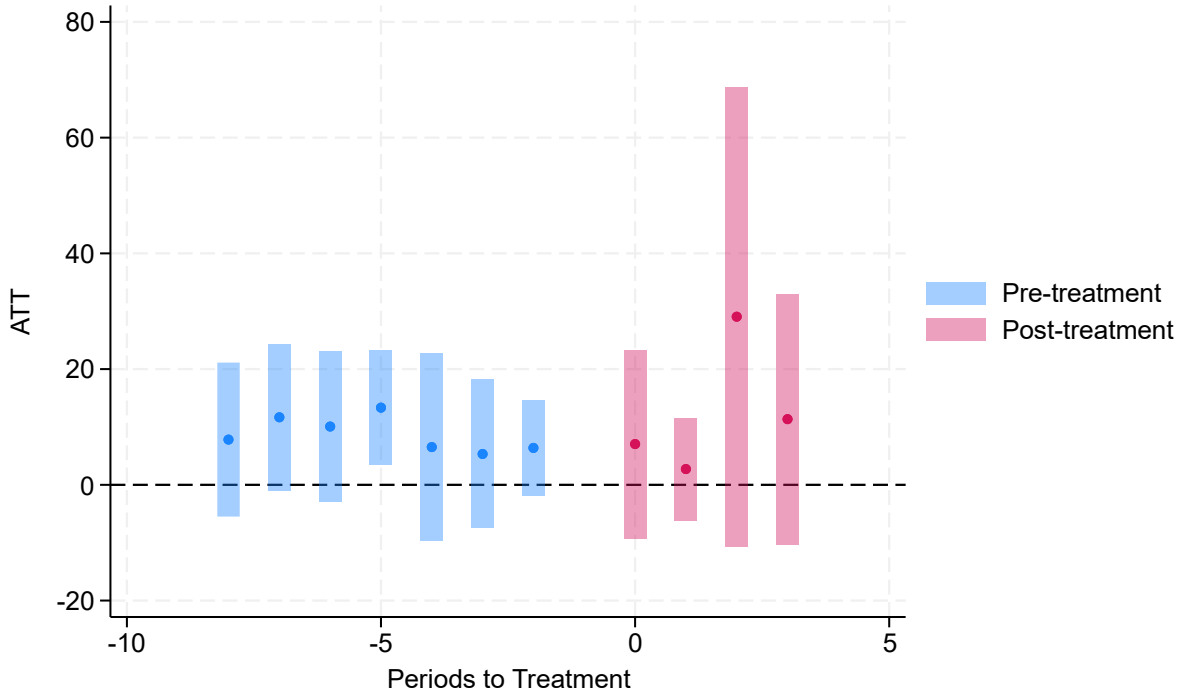
Fig. N-1. Event study, eviction filing rates in Brooklyn Center block groups relative to never-treated portions of the adjusted suburban sample (using HOME Line data).



Note: Figure shows difference-in-differences event study, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. This specification was calculated using data from HOME Line. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction filing rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level eviction filings, aggregated into a panel of eviction filings by block group in 30-day periods. Eviction data drawn from HOME Line. Geocoded and aggregated by block group using ArcGIS Pro. This work not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Appendix O: Placebo test for DiD, fake treatment date

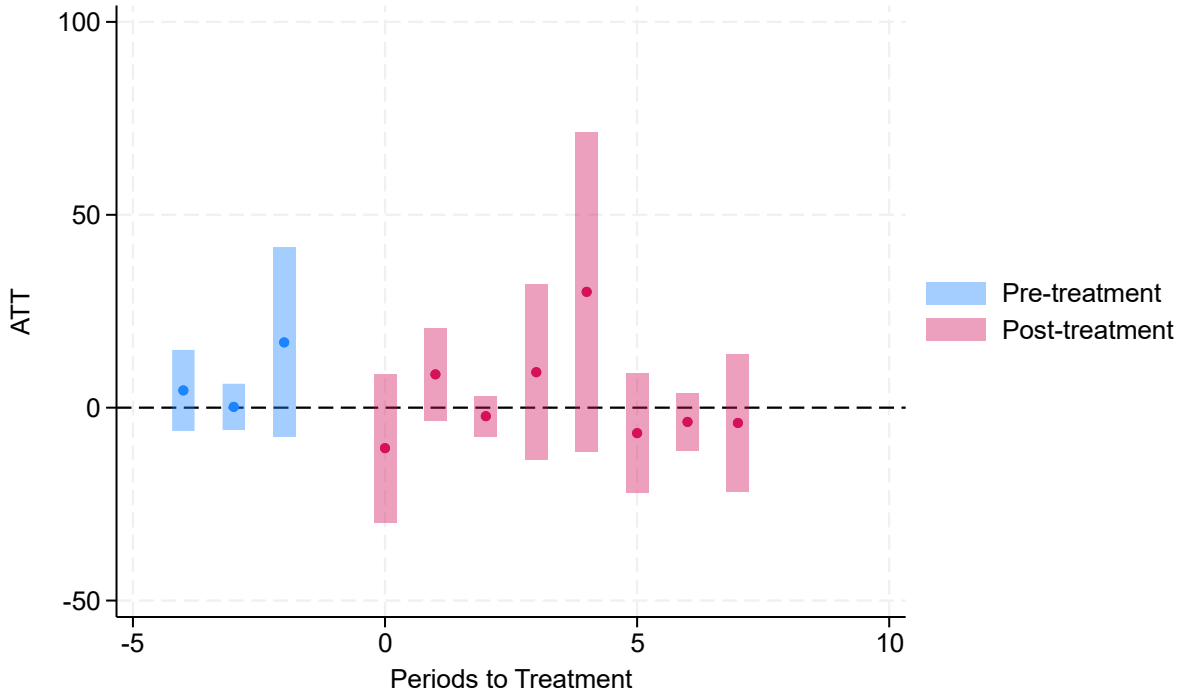
Fig. O-1. Placebo test: event study, eviction rates with fake treatment time in period four.



Note: Figure shows a placebo test with a fake treatment date in period four (about four months after the policy was adopted). This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

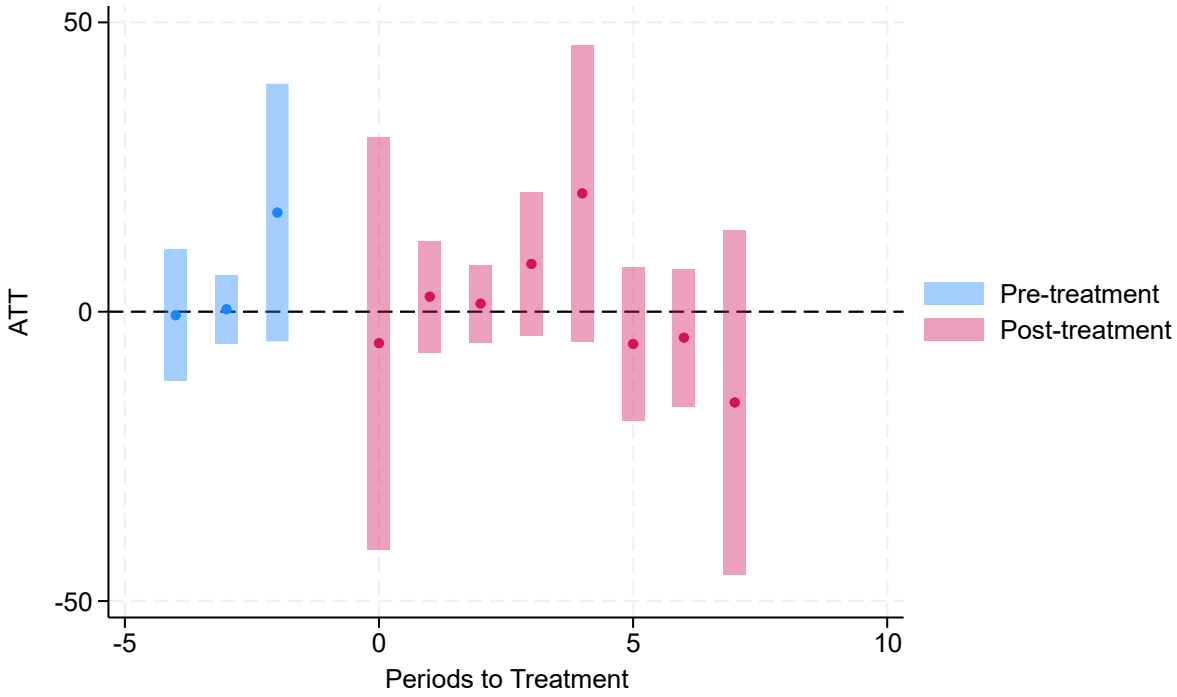
Appendix P: Placebo tests for DiD, fake treated units

Fig. P-1. Placebo test: event study, Brooklyn Park as fake treated unit.



Note: Figure shows a placebo test with Brooklyn Park as the treated unit. This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Brooklyn Center is excluded here, to facilitate the placebo test. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

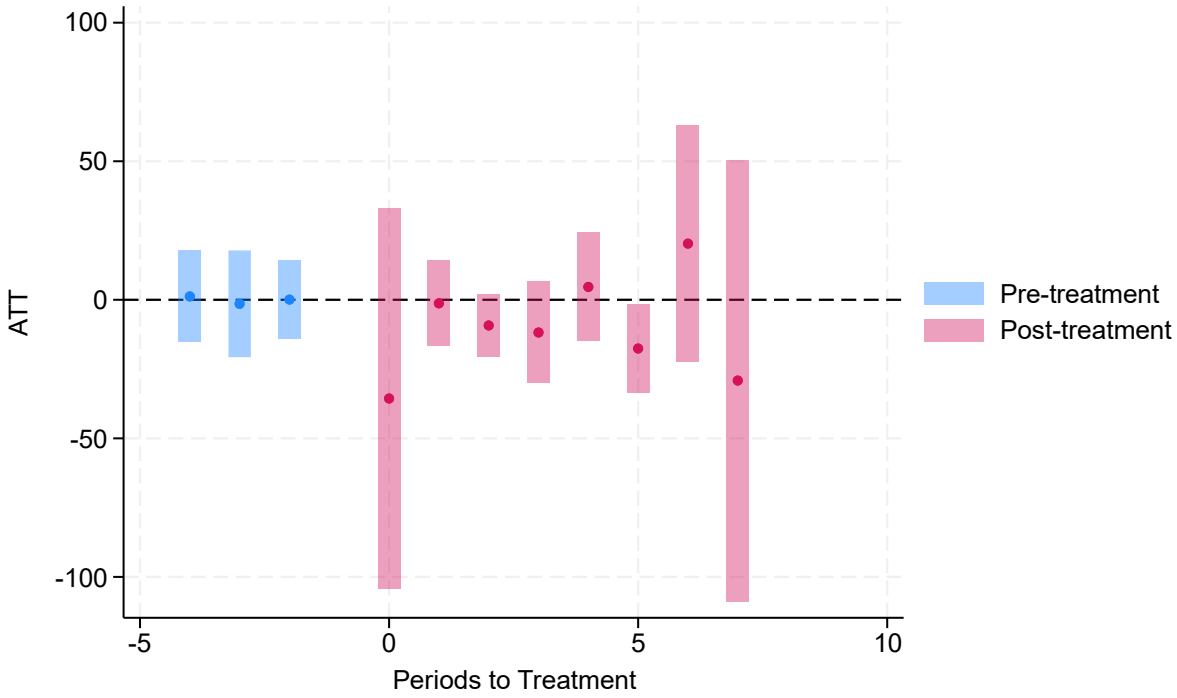
Fig. P-2. Placebo test: event study, border cities (Brooklyn Park, Crystal, and Robbinsdale) as fake treated unit.



Note: Figure shows a placebo test where block groups with centroids located within cities bordering Brooklyn Center (Brooklyn Park, Crystal, and Robbinsdale) are the treated unit. This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Brooklyn Center is excluded here, to facilitate the placebo test. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

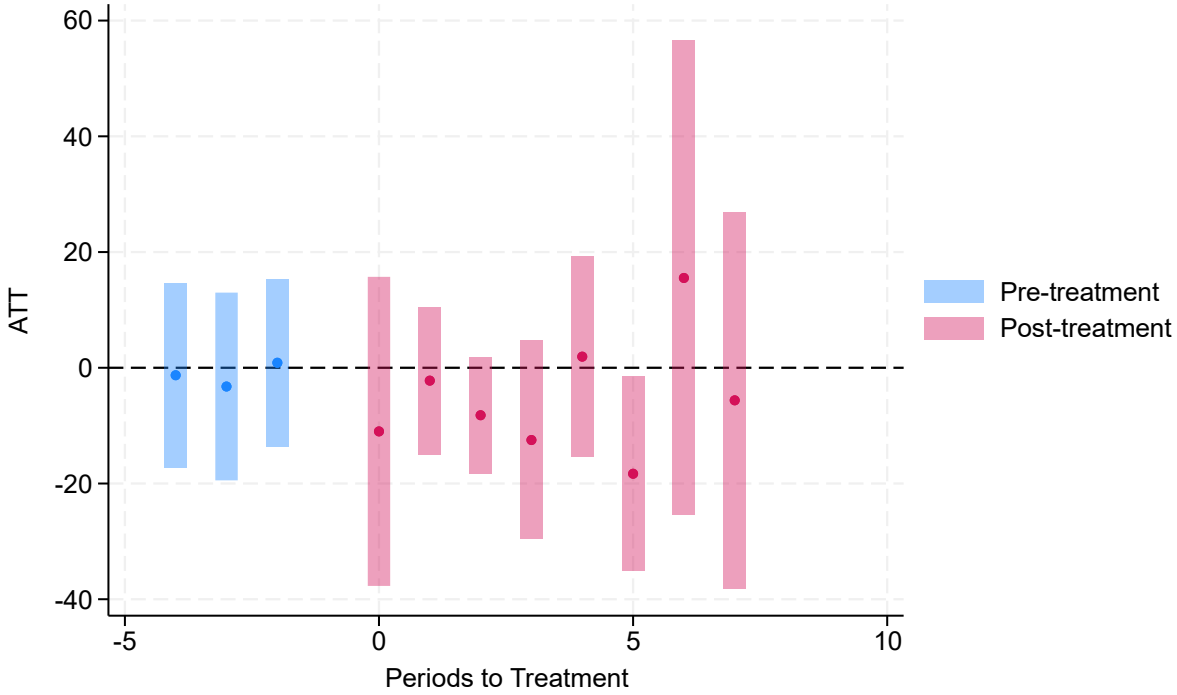
Appendix Q: Robustness checks for DiD, nearby cities excluded from sample

Fig. Q-1. Robustness check, event study with border cities (Brooklyn Park, Crystal, and Robbinsdale) excluded from the sample.



Note: Figure shows a robustness check for a modified sample, where block groups with centroids located within cities bordering Brooklyn Center (Brooklyn Park, Crystal, and Robbinsdale) are excluded. This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Brooklyn Park, Crystal, and Robbinsdale block groups are excluded to facilitate this robustness check. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

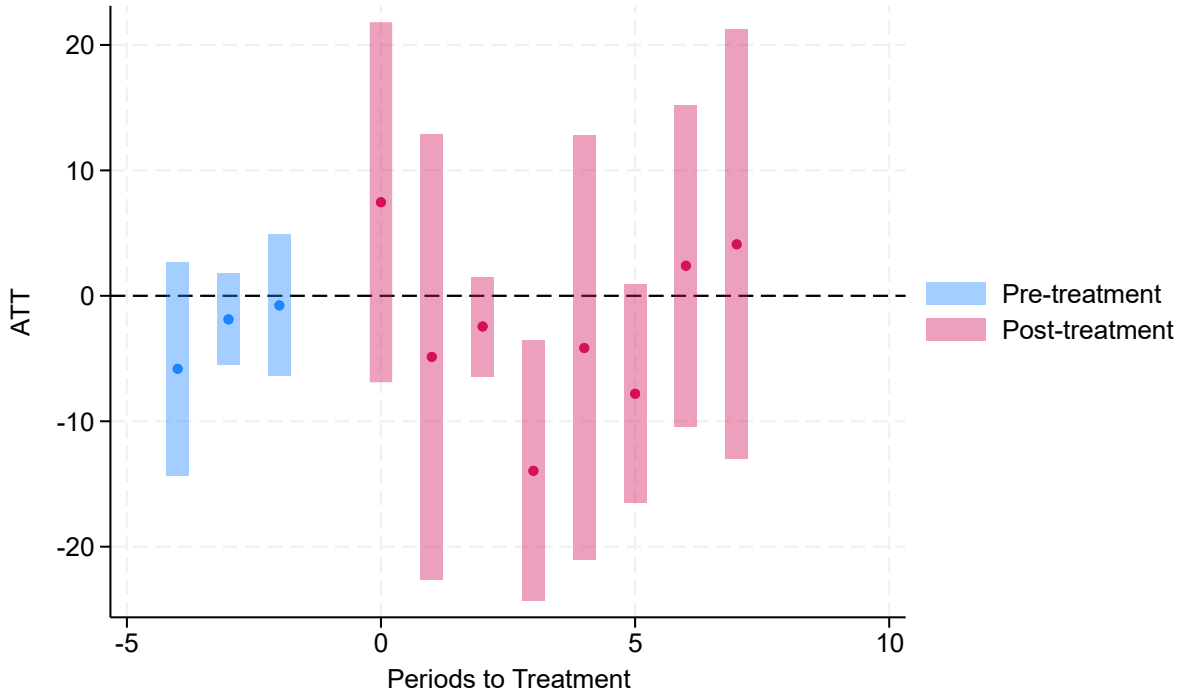
Fig. Q-2. Robustness check, event study with Brooklyn Park excluded from the sample.



Note: Figure shows a robustness check for a modified sample, with Brooklyn Park excluded. This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Brooklyn Park block groups are excluded to facilitate this robustness check. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Appendix R: Robustness check for DiD, sample restricted to block groups with 100+ renter households

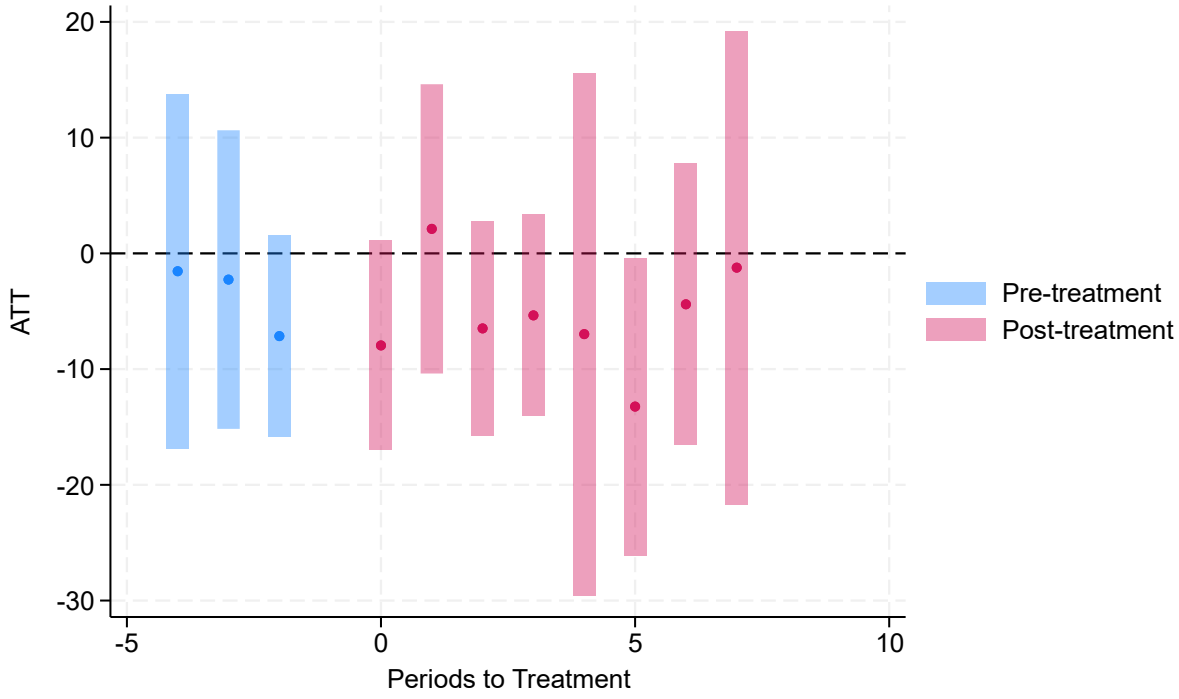
Fig R-1. Robustness check, event study using only block groups with 100+ renter-occupied housing units.



Note: Figure shows a robustness check for a modified sample, keeping only those block groups with 100 or more renter-occupied housing units (as of the 2015-19 ACS). is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2015-19 by block group) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The suburban sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis uses the adjusted suburban sample, which restricts the suburban sample to remove all block groups with mobile home renters, and remove the top decile of block groups by group quarters as a share of the population. Sample further restricted to remove block groups with fewer than 100 renter-occupied housing units. Eviction rate calculated per 10,000 renter-occupied housing units in block group, using ACS 2015-19 data accessed via Social Explorer. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by block group in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by block group using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Appendix S: Robustness check for DiD, data aggregated by 2020 Census tract

Fig. S-1. Robustness check, event study using 2020 tracts and 2017-21 ACS data for covariates.



Note: For this figure, data was aggregated by 2020 Census tract boundaries, and covariates were drawn from the 2017-21 ACS. This is a difference-in-differences event study focusing on eviction rates, reporting pre-trends and ATT(t) for 30-day periods before and after the adoption of the Tenant Protection ordinance on February 28, 2022. February 28 is the first day in period 0. Pre-treatment covariates (from ACS 2017-21 by tract) used for inverse probability weighting: *natural log of median household income; fraction of adults 25+ with less than high school education; fraction of adults 25+ with bachelor's degree or higher; fraction of renter householders who are Hispanic; fraction of renter householders who are white non-Hispanic; fraction of renters who pay 30-49% of income for housing; fraction of renters who pay 50% or more of income for housing; renter-occupied housing units as a share of occupied housing units*. The sample was constructed using the portions of Hennepin County other than Minneapolis and St. Louis Park. This analysis adjusts the sample by removing tracts with mobile home renters, and removing tracts in the top decile by tract of group quarters population as a share of the total population. ACS data on mobile home renter populations drawn from IPUMS NHGIS. Eviction rate calculated per 10,000 renter-occupied housing units in tract, using ACS 2017-21 data accessed via the Census website. Figure created using the *csdid* Stata package, following the approach of Callaway and Sant'Anna (2021) and Sant'Anna and Zhao (2020). This analysis focuses on household-level evictions, aggregated into a panel of evictions by tract in 30-day periods. Eviction data drawn from Minnesota Judicial Branch via CURA. Duplicate records of evictions filed on the same date with the same address or case number removed. Geocoded with ggmap and Google Maps API. Data aggregated by tract using US Census Bureau Data API. This work uses the Census Bureau Data API but is not endorsed or certified by the Census Bureau. Standard errors calculated via 10,000 bootstrap replications; bars show 95% confidence intervals.

Flattening the Eviction Curve:
A Quasi-Experimental Evaluation of the Brooklyn Center Tenant Protection Ordinance

MPP Professional Paper

In Partial Fulfillment of the Master of Public Policy Degree Requirements
Hubert H. Humphrey School of Public Affairs
University of Minnesota

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Signature below of Committee Chair certifies successful completion of oral presentation and completion of final written paper:

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Abstract

This paper uses two quasi-experimental methods—synthetic control (SC) and difference-in-differences (DiD)—to evaluate the effects of the 2022 Brooklyn Center Tenant Protection Ordinance. The ordinance was adopted at a time when eviction filings were on the rise across the state. Descriptive statistics provide an indication that after the ordinance was adopted, Brooklyn Center's eviction rate did not increase by as much as the eviction rate in other parts of suburban Hennepin County. For SC models, I compared Brooklyn Center to most other Hennepin County cities. I found statistically significant evidence that the ordinance reduced eviction rates in the period 37-48 weeks after policy adoption. This result survived several placebo tests (though it was sensitive to whether Brooklyn Park was included in the donor pool). Results for filing rates did not survive all placebo tests. For DiD, I drew from a sample of most block groups in suburban Hennepin County. Conditioning on pre-treatment covariates via doubly robust DiD, I found the policy brought reduced eviction rates and filing rates in some of the first eight months after policy adoption. DiD models survived a wide variety of robustness checks. SC and DiD provided consistent evidence of reduced eviction rates in some periods of time. The two methods produced mixed evidence on filing rates, and did not produce strong evidence of policy effects for other outcomes. This paper concludes that when evictions spiked across Minnesota following the expiration of COVID-19 eviction moratorium policies, the City of Brooklyn Center flattened the eviction curve.

Keywords: Eviction, Displacement, Eviction Moratorium, COVID-19, Just Cause, Pre-Eviction Notice, Housing, Landlord-Tenant, Tenant Protections, Policy, Local Policy, Public Policy, Brooklyn Center, Hennepin County, Effectiveness, Causal, Causal Inference, Evaluation, Impact Evaluation, Program Evaluation, Quasi-Experimental, Difference-in-Differences, Event Study, Synthetic Control