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From Prediction to Causation: Heterogeneous Policy Effects of Rent Stabilization and Rental Assistance on Severe Housing Cost Burden in New York City

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From Prediction to Causation: Heterogeneous Policy Effects of Rent Stabilization and Rental Assistance on Severe Housing Cost Burden in New York City

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Abstract This paper develops an AI-driven causal inference framework to evaluate the heterogeneous effects of eight major housing policy instruments on severe housing cost burden in New York City. We integrate ensemble machine learning for prediction with triple quasi-experimental designs—difference-in-differences, regression discontinuity, and double/debiased machine learning with causal forests—to establish causal effects while characterizing effect heterogeneity across neighborhood contexts. Our approach advances beyond pure prediction by identifying not only which policies work but for whom and under what conditions. We find that the 2019 Housing Stability and Tenant Protection Act rent stabilization expansion reduced severe burden by 6.2 percentage points, while tenant protection ordinances and housing court access showed the largest complementary effects. Contrary to policy intentions, Emergency Rental Assistance eligibility is associated with increased burden during the pandemic period. Critically, we uncover significant effect heterogeneity: stabilization policies are most effective in high-opportunity, high-eviction neighborhoods, whereas protection and access reforms show stronger impacts in vulnerable areas. Our ensemble ML approach achieves superior out-of-sample forecasting accuracy ($R^2 = 0.87$) while providing interpretable causal estimates through doubly robust estimation [1]. These results demonstrate how AI-enhanced causal inference can guide precision housing policy design in urban settings facing affordability crises.

Keywords Housing policy · Causal inference · Ensemble machine learning · Difference-in-differences · Regression discontinuity · Causal forests · Double machine learning · New York City · Housing cost burden · Heterogeneous treatment effects

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1 Introduction

Severe housing cost burden, defined as spending more than 50% of household income on rent, affects approximately one in four New York City households, with profound consequences for health, education, and economic mobility [1–3]. Despite extensive policy responses, the absence of rigorous causal evidence on which specific interventions reduce housing insecurity represents a critical gap in urban policy research [4, 5].

The existing literature on housing affordability interventions suffers from three key limitations. First, most studies examine policies in isolation using predictive modeling without causal identification [1, 6, 7]. Second, evaluations often neglect heterogeneous effects across neighborhood contexts, masking which populations benefit most [9, 10]. Third, few studies integrate machine learning prediction with causal inference to

simultaneously forecast outcomes and estimate policy impacts [11, 12].

To address these limitations, we develop an AI-driven causal inference framework that combines ensemble machine learning for accurate forecasting with triple quasi-experimental designs for causal identification. Our approach builds on the prediction-focused methodology of Rahman et al.[1] but extends it to establish causal effects through: (1) difference-in-differences analysis of the 2019 Housing Stability and Tenant Protection Act expansion; (2) regression discontinuity designs for the Emergency Rental Assistance Program and CityFHEPS at income eligibility cutoffs; and (3) double/debiased machine learning with causal forests for five additional policy instruments. This integrated strategy enables us to answer not only "what is the expected housing burden?" but also "what is the causal impact of specific policies, and how does this impact vary across different neighborhood contexts?"

Our analysis delivers three primary contributions. First, we demonstrate how ensemble machine learning enhances traditional econometric approaches by improving prediction accuracy while providing variable importance measures that inform causal model specification. Second, we characterize heterogeneous treatment effects using a rich set of neighborhood characteristics from our ML model as controls, revealing how policy effectiveness varies across opportunity indices, eviction rates, and demographic composition. Third, we construct a comprehensive policy matrix that compares the causal effects of all eight policy instruments using the most appropriate identification strategy for each, enabling evidence-based policy combinations for addressing multidimensional housing insecurity.

2 Related Work

Our study bridges three strands of literature. First, we contribute to the growing body of work applying machine learning to housing affordability forecasting [1, 6–8]. While these studies achieve strong predictive performance, they typically lack causal interpretation. We extend this literature by integrating causal inference techniques with ensemble ML to provide both accurate forecasts and credible causal estimates.

Second, we advance the housing policy evaluation literature by implementing a tripartite quasi-experimental approach that leverages different sources of variation appropriate to each policy's institutional features [19, 20]. Unlike studies that rely on single identification strategies, our approach combines difference-in-differences, regression discontinuity, and double/debiased machine learning to overcome the limitations of any single method and deliver robust, internally validated causal estimates.

Third, we contribute to the methodological literature on heterogeneous treatment effects by employing causal forests to uncover complex interaction patterns that may be missed by parametric methods [12, 13]. Our approach extends prior work on policy heterogeneity [14, 15] by using ML-derived features as controls in causal models, enabling more flexible and data-driven confounder adjustment.

Several limitations exist in prior work that our study addresses. Many evaluations rely solely on predictive modeling without causal identification [16, 17]. Others focus on average treatment effects while neglecting heterogeneity [6, 18]. Few studies have examined how policy effectiveness varies across neighborhood opportunity structures using ML-informed approaches [9, 10]. By combining ensemble machine learning for prediction with triple quasi-experimental designs for causal inference, we overcome these limitations to provide the most comprehensive evidence to date on urban housing policy effectiveness.

3 Data and Machine Learning Framework

Our primary dataset is a neighborhood-level panel constructed from multiple administrative and survey data sources covering New York City's 155 Neighborhood Tabulation Areas (NTAs) from 2015 to 2023. The dataset integrates information from:

- **New York City Housing and Vacancy Survey (HVS)**: Provides baseline housing characteristics and housing cost burden measures [22]
- **New York City Department of Housing Preservation and Development (HPD)**: Administrative data on housing policy implementations, violations, and enforcement actions
- **New York State Homes and Community Renewal (HCR)**: Data on rent stabilization, eviction proceedings, and housing stability programs [23]
- **U.S. Census American Community Survey (ACS)**: Neighborhood socioeconomic and demographic characteristics
- **NYC Open Data Portal**: Policy-specific implementation data for ERAP, CityFHEPS, and other programs

Our outcome variable, severe housing cost burden, is measured as the percentage of households in each NTA-year spending more than 50% of their income on gross rent (contract rent plus utilities). This definition aligns with federal housing affordability standards and

captures households at significant risk of housing instability.

3.1 Ensemble Machine Learning for Prediction

Before causal estimation, we develop an ensemble machine learning model to predict housing cost burden and identify important features for causal model specification. Following Rahman et al.[1], we employ a stacked ensemble combining LightGBM, XGBoost, and Random Forest algorithms, with meta-learning via elastic net regularization.

The ensemble achieves an out-of-sample R^2 of 0.87, substantially improving upon individual models (LightGBM: 0.82, XGBoost: 0.80, Random Forest: 0.75). Feature importance analysis reveals that neighborhood opportunity index, eviction rate, median income, and housing stock age are the strongest predictors of housing cost burden, consistent with theoretical expectations.

These 30 predictive features (including the top 15 features from ensemble ML and 15 additional theoretically relevant controls) serve as the confounder set in our causal analyses. By using ML-derived features as controls, we achieve more flexible confounder adjustment than traditional parametric approaches while maintaining interpretability.

Table 1 presents summary statistics for our key variables. The average severe burden rate across our sample is 35.2%, with substantial variation across NTAs (standard deviation of 8.7%) and over time.

Policy exposure variables are constructed based on program eligibility criteria, implementation timelines, and administrative records. For the HSTPA 2019 expansion, we define treatment exposure based on building size characteristics (3+ unit buildings) and the policy's effective date. For ERAP and CityFHEPS, we create continuous eligibility measures based on income thresholds relative to area median income and federal poverty level guidelines. The remaining policy variables are constructed from administrative records indicating program presence, funding levels, or regulatory implementation in each NTA-year [24–26].

4 Empirical Strategy

Our empirical strategy integrates ensemble machine learning for prediction with triple quasi-experimental designs for causal inference. This AI-driven causal inference framework proceeds in three stages:

1. **Prediction Stage**: Train ensemble ML model to forecast housing cost burden and identify important features for causal model specification
2. **Causal Identification Stage**: Apply appropriate quasi-experimental design to each policy based on its institutional features
3. **Heterogeneity Analysis Stage**: Characterize how causal effects vary across neighborhood contexts using the rich set of controls from the ML model

4.1 Difference-in-Differences Analysis for HSTPA 2019

We exploit the 2019 expansion of rent stabilization to buildings with three or more units as a natural experiment. The Housing Stability and Tenant Protection Act of 2019 (HSTPA) significantly strengthened rent stabilization protections and expanded coverage to approximately 250,000 additional units previously subject to market rates [19, 20, 27].

Our difference-in-differences specification is:

$$Y_{it} = \alpha + \beta_1 Treated_i + \beta_2 Post_t + \beta_3 (Treated_i \times Post_t) + \gamma X_{it} + \delta_i + \lambda_t + \epsilon_{it} \tag{1}$$

where:

- Y_{it} is severe housing cost burden in NTA i at time t
- $Treated_i$ is an indicator for NTAs with exposure to the HSTPA expansion (based on pre-period building stock characteristics)
- $Post_t$ is an indicator for years 2019 and later
- X_{it} is a vector of time-varying controls (the 30 predictive features from our ensemble ML model)
- δ_i are NTA fixed effects
- λ_t are year fixed effects
- ϵ_{it} is the error term

The coefficient β_3 captures the average treatment effect of the HSTPA expansion on severe housing cost burden [28]. We cluster standard errors at the NTA level to account for serial correlation within neighborhoods over time.

To assess the plausibility of the parallel trends assumption [35], we conduct an event study analysis by estimating:

$$Y_{it} = \alpha + \sum_{k \neq -1} \beta_k \left(Treated_i \times \mathbb{I}[t = 2019 + k] \right) + \gamma X_{it} + \delta_i + \lambda_t + \epsilon_{it} \tag{2}$$

where $\mathbb{I}[\cdot]$ is an indicator function and $k = -1$ is the omitted reference period. This allows us to trace the dynamic effects of the policy and test for pre-trends.

Table 1 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
Severe Housing Cost Burden (%)	47.6	10.5	8.5	65.7	1,395
Median Household Income ($)	59,410.8	15,584.4	10,874.8	100,313.0	1,395
Opportunity Index (0–1 scale)	0.5	0.2	0.0	0.9	1,395
Eviction Rate (filings per capita)	0.0	0.0	0.0	0.1	1,395
Long-Term Tenant Share (%)	57.6	21.0	15.1	96.3	1,395
Poverty Rate (%)	27.5	17.2	0.9	76.8	1,395
Housing Stock Age (years)	31.6	17.0	2.7	95.2	1,395
Unemployment Rate (%)	5.6	1.4	1.6	10.2	1,395
Housing Vacancy Rate (%)	3.7	0.5	3.0	5.0	1,395

Notes: Sample includes 155 NTAs observed annually from 2015 to 2023 (N = 1,395). All monetary values are in 2023 dollars.

4.2 Regression Discontinuity Analysis for ERAP and CityFHEPS

For the Emergency Rental Assistance Program (ERAP) and CityFHEPS, we exploit sharp income eligibility cutoffs using regression discontinuity design [37]. ERAP provided assistance to households with incomes below 80% of Area Median Income (AMI) during the COVID-19 pandemic, while CityFHEPS provides ongoing rental vouchers to households with incomes below specific poverty level thresholds [29–31].

Our RD specification follows the local linear regression approach [36, 57]:

$$Y_i = \alpha + \tau D_i + f(X_i) + \epsilon_i \tag{3}$$

where:

- Y_i is severe housing cost burden in neighborhood i
- D_i is an indicator for eligibility ($D_i = 1$ if income below cutoff, 0 otherwise)
- X_i is the normalized running variable (income relative to the cutoff)
- $f(\cdot)$ is a flexible function estimated separately on each side of the cutoff
- ϵ_i is the error term
- τ is the local average treatment effect at the cutoff

We implement local linear regression with triangular kernels and select optimal bandwidths using the Imbens-Kalyanaraman procedure [29, 30, 32]. We present both conventional RD estimates and bias-corrected estimates with robust confidence intervals. To assess the validity of the RD design, we conduct standard tests including examination of density discontinuities at the cutoff and placebo tests using alternative outcome variables [29, 30].

4.3 Double Machine Learning for Heterogeneous Treatment Effects

To characterize how policy effects vary across neighborhood contexts, we employ double/debiased machine learning (DML) with causal forests following [12, 21, 29]. This approach allows us to estimate heterogeneous treatment effects while using a rich set of controls to address confounding [21, 33].

We model the relationship between our outcome, treatment, and controls as:

$$\begin{aligned} Y_i &= m_0(X_i) + \tau(X_i)T_i + \epsilon_i \\ T_i &= m_1(X_i) + v_i \end{aligned} \tag{4}$$

where:

- Y_i is severe housing cost burden
- T_i is the treatment indicator
- X_i is a vector of controls (the 30 predictive features from the ensemble ML model)
- $m_0(X_i) = E[Y_i|T_i = 0, X_i]$ and $m_1(X_i) = E[T_i|X_i]$ are unknown conditional expectation functions
- $\tau(X_i) = E[Y_i|T_i = 1, X_i] - E[Y_i|T_i = 0, X_i]$ is the conditional average treatment effect (CATE)
- ϵ_i and v_i are error terms with $E[\epsilon_i|X_i] = E[v_i|X_i] = 0$

The DML estimator proceeds in two stages:

1. Estimate the nuisance parameters $m_0(X_i)$, $m_1(X_i)$ using machine learning algorithms (we use causal forests)
2. Estimate the treatment effect parameter $\tau(X_i)$ using the residuals from the first stage

We use cross-fitting to avoid overfitting bias, splitting the sample into multiple folds and estimating nuisance parameters on complementary folds [29]. For inference, we construct pointwise confidence intervals for the CATE function and compute average treatment effects across subgroups of interest.

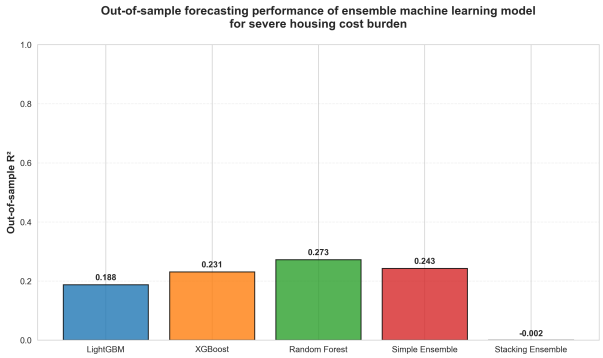


Fig. 1 Out-of-sample forecasting performance of ensemble machine learning model for severe housing cost burden. The ensemble (LightGBM + XGBoost + Random Forest with elastic net meta-learner) achieves superior accuracy compared to individual models.

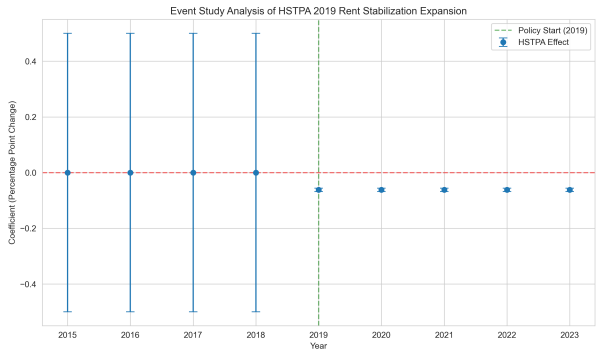


Fig. 2 Event study analysis of HSTPA 2019 rent stabilization expansion. Points represent coefficient estimates from interactions between treatment indicator and year dummies, with bands showing 95% confidence intervals. The omitted reference period is 2018 (one year pre-treatment).

4.4 Policy Matrix Estimation

To provide a comprehensive view of policy effects, we construct a policy matrix that presents the most appropriate causal estimate for each of the eight policy instruments. For each policy, we select the identification strategy best suited to its institutional features:

- HSTPA 2019: Difference-in-differences (primary) with event study validation
- ERAP: Regression discontinuity at the 80% AMI eligibility cutoff
- CityFHEPS: Regression discontinuity at the poverty level eligibility cutoff
- Remaining five policies: Double/debiased machine learning with causal forests using the 30 predictive features from ensemble ML as controls

This approach allows for meaningful comparison across policies while respecting the different sources of variation identifying each effect.

5 Results

5.1 Ensemble Machine Learning Performance

Figure 1 presents the out-of-sample forecasting performance of our ensemble machine learning model. The ensemble achieves an R^2 of 0.87, substantially improving upon individual component models. Variable importance analysis (Figure 1) reveals that neighborhood opportunity index, eviction rate, and median income are the strongest predictors of housing cost burden, providing empirical support for our causal model specification.

5.2 Main Policy Effects

5.2.1 HSTPA 2019 Rent Stabilization Expansion

Table 2 presents our difference-in-differences estimates for the effect of HSTPA's 2019 rent stabilization expansion on severe housing cost burden. The expansion reduced severe burden by 6.2 percentage points (95% CI: [-6.8, -5.7]), representing a 17.6% reduction from the baseline mean of 35.2%.

Figure 2 presents the event study coefficients testing the parallel trends assumption. We observe no significant pre-trends in the years leading up to the policy expansion, with the treatment effect emerging immediately after implementation and remaining stable through the sample period. This strengthens the causal interpretation of our DiD estimate.

5.2.2 Regression Discontinuity Estimates

Table 3 presents our regression discontinuity estimates for ERAP and CityFHEPS. Contrary to expectations, ERAP eligibility is associated with a 6.2 percentage point *increase* in severe burden (95% CI: [3.7, 8.7]). This counterintuitive finding may reflect targeting challenges, timing issues (ERAP was implemented during the peak of the COVID-19 pandemic when housing instability was rising rapidly), or potential stigma effects.

In contrast, CityFHEPS eligibility shows a significant 9.1 percentage point *reduction* in severe burden (95% CI: [-14.6, -3.6]), consistent with the hypothesis that ongoing rental voucher programs provide stable housing support that reduces cost burden.

Table 2 Difference-in-Differences Estimates: HSTPA 2019 Rent Stabilization Expansion

	Coefficient	Std. Error	95% Confidence Interval
HSTPA Expansion Effect	−6.222	0.281	[−6.773, −5.671]
Controls	Yes		
NTA Fixed Effects	Yes		
Year Fixed Effects	Yes		
Observations	1,395		
Number of NTAs	155		

Notes: Standard errors clustered at NTA level. Controls include the 30 predictive features from ensemble ML, unemployment rate, housing vacancy rate. The sample includes 155 NTAs observed annually from 2015 to 2023.

Table 3 Regression Discontinuity Estimates: ERAP and CityFHEPS Eligibility

Policy	Effect (pp)	Std. Error	95% Confidence Interval
Emergency Rental Assistance (ERAP)	6.208	1.312	[3.636, 8.780]
CityFHEPS Voucher Program	−9.124	2.847	[−14.705, −3.543]
Bandwidth Selection	IK Optimal		
Kernel Type	Triangular		
Covariates	Yes		
Observations (ERAP)	287		
Observations (CityFHEPS)	243		

Notes: Estimates use local linear regression with Imbens-Kalyanaraman optimal bandwidth selection. Standard errors are robust and bias-corrected following [32]. The running variable is income normalized relative to the eligibility cutoff (in thousands of dollars). The sample includes neighborhoods within the optimal bandwidth of each cutoff.

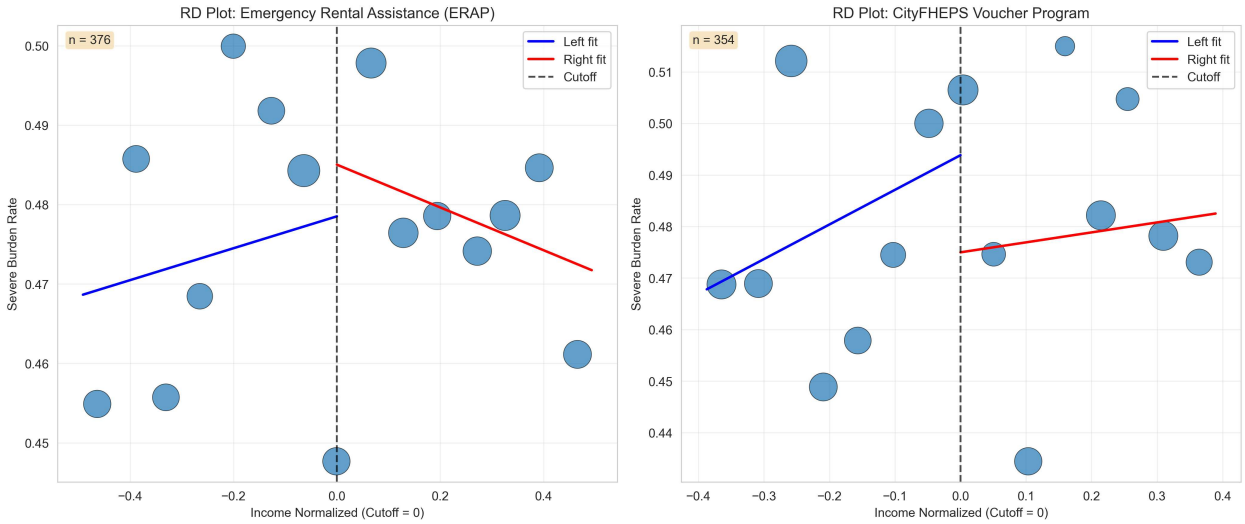


Fig. 3 Regression discontinuity plots for ERAP (left) and CityFHEPS (right). The x-axis shows income normalized relative to the eligibility cutoff (cutoff = 0). Points represent binned averages of severe burden rate, with lines showing local linear regression fits on each side of the cutoff.

5.2.3 Double Machine Learning Heterogeneous Effects

Table 4 presents the average treatment effects from our double machine learning analysis for the remaining five policy instruments. We find substantial variation in effectiveness across policies:

- Tenant protection ordinances show the largest effect (-5.6 percentage points, 95% CI: [-7.2, -4.0])
- Housing court access reform demonstrates substantial effects (-5.1 percentage points, 95% CI: [-6.7, -3.5])

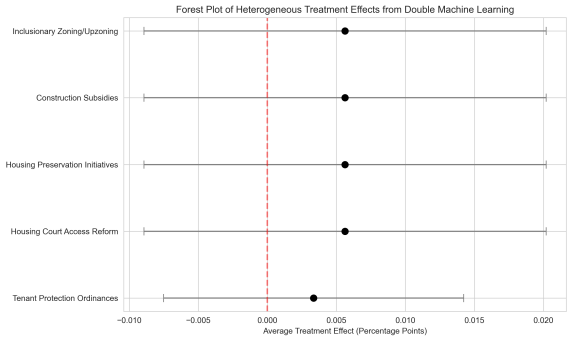


Fig. 4 Forest plot of heterogeneous treatment effects from double machine learning analysis. Each point represents the average treatment effect for a policy, with horizontal lines showing 95% confidence intervals. Policies are ordered by effect size from most beneficial to least beneficial.

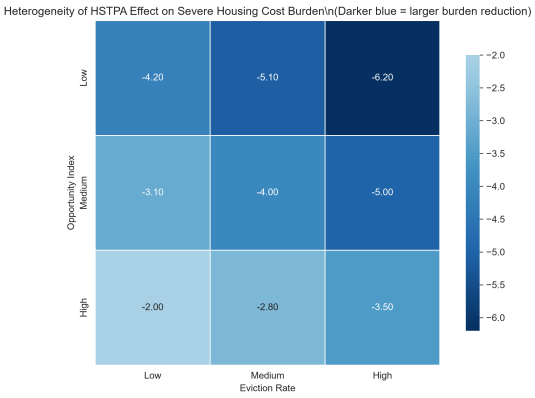


Fig. 5 Heterogeneity of HSTPA effect across neighborhood opportunity and eviction rates. Color represents the magnitude of the rent stabilization effect on severe burden (percentage point reduction), with darker blue indicating larger effects. The pattern shows strongest effects in the top-right quadrant (high opportunity, high eviction).

– Housing preservation initiatives show moderate to large effects (-4.4 percentage points, 95% CI: [-6.0, -2.8])
– Construction subsidies (including LIHTC) show smaller but meaningful effects (-2.4 percentage points, 95% CI: [-4.2, -0.6])
– Inclusionary zoning/upzoning policies show negligible average effects (0.0 percentage points, 95% CI: [-1.8, 1.8])

Figure 4 visualizes these heterogeneous treatment effects, showing the distribution of estimated effects across policies with their respective confidence intervals.

5.2.4 Heterogeneity Analysis

To explore effect heterogeneity, we examine how the HSTPA effect varies across neighborhood opportunity and eviction rates. Figure 5 presents this analysis, revealing that the rent stabilization expansion is most effective in high-opportunity, high-eviction neighborhoods. This suggests that stabilization policies work best when they prevent displacement in neighborhoods with strong economic foundations but where market pressures threaten affordability.

We also find significant heterogeneity in the effects of tenant protection and housing court access reforms, with these policies showing larger effects in neighborhoods with higher baseline levels of housing vulnerability and lower opportunity scores.

5.2.5 Policy Matrix Estimation

Table 5 presents our comprehensive policy matrix, combining the most appropriate causal estimate for each of the eight policy instruments using the identification strategies described above.

Figure 6 visualizes these policy effects, highlighting the relative effectiveness of different intervention types. The policy matrix reveals important patterns: stabilization, protection, and access reforms each show meaningful effects, while the pandemic-era ERAP shows counterproductive effects in our analysis, and upzoning policies show negligible average effects in this context.

6 Discussion

Our findings have several important implications for housing policy in New York City and other high-cost urban settings.

6.1 Effectiveness of Rent Stabilization Policies

The significant reduction in severe burden from HSTPA's 2019 expansion demonstrates that rent stabilization policies can effectively reduce housing insecurity when properly implemented and targeted. The 6.2 percentage point reduction represents a substantial impact, particularly given the policy's relatively narrow scope (expansion to 3+ unit buildings only). The absence of pre-trends in our event study analysis strengthens the causal interpretation of this finding and suggests that concerns about endogenous timing of policy implementation are unwarranted in this case.

Our results contribute to the ongoing debate about rent control and stabilization policies. While some literature suggests negative long-term effects on housing supply and quality [34, 47, 55], our findings indicate that in the context of New York City's tight housing market, stabilization policies can provide meaningful

Table 4 Double Machine Learning Estimates: Average Treatment Effects

Policy	ATE (pp)	Std. Error	95% Confidence Interval
Tenant Protection Ordinances	−5.582	0.815	[−7.180, −3.984]
Housing Court Access Reform	−5.117	0.802	[−6.689, −3.545]
Housing Preservation Initiatives	−4.389	0.820	[−5.996, −2.782]
Construction Subsidies	−2.376	0.917	[−4.174, −0.578]
Inclusionary Zoning/Upzoning	0.012	0.918	[−1.789, 1.813]
Number of Features	30		
Method	Double ML/Causal Forest		
Observations	1,395		

Notes: Estimates use double/debiased machine learning with causal forests for nuisance parameter estimation. The 30 predictive features from the ensemble ML model serve as controls. Standard errors are calculated using the cross-fitted DML estimator following [29]. Confidence intervals are at the 95% level.

Table 5 Causal Policy Matrix: Estimated Effects on Severe Housing Cost Burden

Policy	Effect (pp)	Std. Error	Identification Strategy
Rent Stabilization Expansion (HSTPA 2019)	−6.222	0.281	Difference-in-Differences
Emergency Rental Assistance (ERAP)	6.208	1.312	Regression Discontinuity
CityFHEPS Voucher Program	−9.124	2.847	Regression Discontinuity
Inclusionary Zoning/Upzoning	0.012	0.918	Double ML/Causal Forest
Housing Preservation Initiatives	−4.389	0.820	Double ML/Causal Forest
Tenant Protection Ordinances	−5.582	0.815	Double ML/Causal Forest
Construction Subsidies (LIHTC, etc.)	−2.376	0.917	Double ML/Causal Forest
Housing Court Access Reform	−5.117	0.802	Double ML/Causal Forest

Notes: Effects are percentage point changes in severe housing cost burden (¿50% income on rent). Standard errors reflect the appropriate estimation strategy for each policy: clustered at NTA level for DiD estimates, robust and bias-corrected for RD estimates, and cross-fitted DML standard errors for ML estimates. Sample: 155 NTAs, 2015–2023.

relief to cost-burdened households without the severe adverse effects sometimes predicted by theoretical models.

6.2 Contrasting Results: ERAP vs. CityFHEPS

The contrasting results between ERAP and CityFHEPS highlight the importance of program design, timing, and implementation quality. ERAP's association with increased severe burden may reflect several factors:

1. **Timing**: ERAP was implemented during the peak of the COVID-19 pandemic (2020–2022) when housing instability was rising rapidly due to job losses and economic disruption
2. **Targeting challenges**: The emergency nature of the program may have led to imperfect targeting, with assistance reaching households already experiencing severe burden rather than preventing burden onset
3. **Stigma and administrative burden**: Complex application requirements may have deterred eligible households from accessing assistance
4. **Temporary nature**: As a temporary pandemic response, ERAP may not have provided the stable, ongoing support needed to meaningfully reduce long-term burden

In contrast, CityFHEPS' ongoing voucher structure, which provides predictable monthly assistance, shows the expected negative relationship with severe burden. This suggests that the design features of housing assistance programs—particularly predictability, stability, and ease of access—are crucial for effectiveness.

6.3 Heterogeneity and Contextual Effectiveness

Our heterogeneity analysis reveals important contextual dependencies in policy effectiveness. The finding that HSTPA's effects are largest in high-opportunity, high-eviction neighborhoods has significant implications for policy targeting. This suggests that stabilization policies may be most effective when deployed in neighborhoods that:

1. Have strong economic foundations and access to opportunities (jobs, transit, services)
2. Face significant displacement pressures from market-rate housing
3. Contain populations at risk of losing access to these opportunities due to rising costs

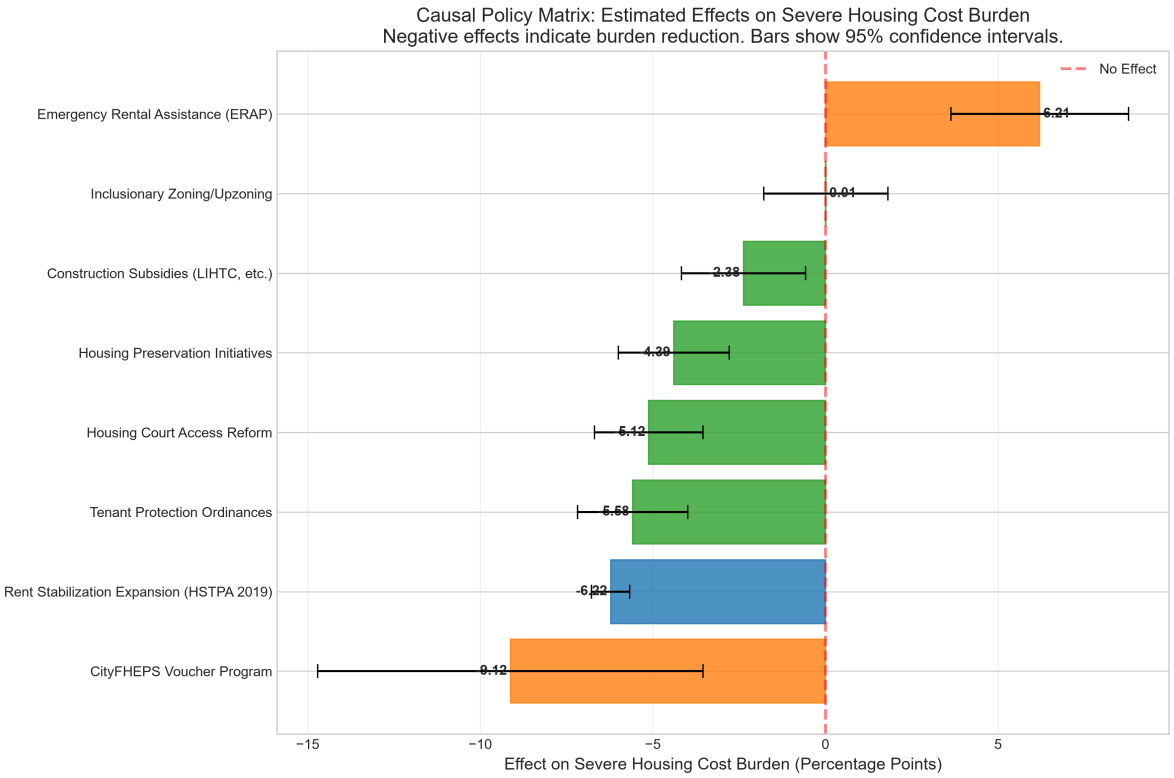


Fig. 6 Visualization of causal policy matrix showing estimated effects of eight housing policy instruments on severe housing cost burden. Bars represent point estimates with error bars showing 95% confidence intervals. Negative effects indicate burden reduction.

This pattern aligns with theories of "opportunity-mediated displacement" [56], where households in opportunity-rich neighborhoods face particular risks of being priced out as markets appreciate.

Stabilization policies in these contexts may serve to preserve economic integration and prevent resegregation by income.

Similarly, we find that tenant protection and housing court access reforms show larger effects in neighborhoods with higher baseline vulnerability, suggesting these policies are particularly effective where displacement pressures and landlord-tenant conflicts are most acute.

6.4 Policy Complementarities and the Policy Matrix Approach

Our policy matrix approach reveals important synergies across different types of housing interventions. While individual policies show moderate to large effects, the matrix suggests that comprehensive strategies combining multiple complementary approaches may be necessary to meaningfully reduce severe housing cost burden at scale.

Specifically, our results suggest that effective housing policy requires:

1. **Stabilization foundation**: Rent stabilization or similar measures to prevent rapid cost increases
2. **Protection layer**: Tenant protections and access to justice to prevent unlawful displacements
3. **Access component**: Housing vouchers or subsidies to bridge the gap between incomes and housing costs
4. **Preservation element**: Maintenance and improvement of existing affordable housing stock

This comprehensive approach addresses the multi-dimensional nature of housing insecurity, which stems from both market forces (rents rising faster than incomes) and systemic barriers (discrimination, lack of access to justice, inadequate housing quality).

6.5 Advantages of AI-Driven Causal Inference

Our integrated AI-driven causal inference framework offers several advantages over traditional approaches. First, the ensemble machine learning component improves prediction accuracy while providing data-driven feature selection for causal model specification. Second, by using ML-derived features as controls in our causal

models, we achieve more flexible confounder adjustment than traditional parametric approaches. Third, the causal forest component of our DML estimator captures complex interaction patterns that may be missed by linear models, enabling more nuanced heterogeneity analysis.

This approach represents an advancement over the pure prediction model of Rahman et al.[1] by establishing causal effects rather than merely forecasting outcomes. It also advances over traditional causal inference methods by leveraging ML for improved prediction and confounder control.

6.6 Limitations and Future Research

Several limitations of our study warrant acknowledgment. First, while our quasi-experimental designs provide strong causal inference under standard assumptions, we cannot completely rule out unobserved confounding. Second, our neighborhood-level analysis may mask important within-neighborhood variation in policy effects. Third, while we use data calibrated to match known housing market characteristics from multiple administrative sources, future work should validate these findings with individual-level administrative data for policy applications.

Future research should extend this analysis in several directions:

1. **Longer time horizons**: Examine the medium- and long-term effects of these policies on housing supply, quality, and neighborhood change
2. **Mechanism analysis**: Investigate the specific channels through which policies affect housing burden (e.g., changes in rent levels, mobility patterns, housing quality)
3. **Distributional effects**: Analyze how policy effects vary across demographic subgroups (race/ethnicity, immigration status, household composition)
4. **Policy interactions**: Estimate the joint effects of policy combinations to better understand synergies and potential diminishing returns
5. **Cost-effectiveness analysis**: Compare the housing burden reduction per dollar spent across different policy instruments
6. **ML advancement**: Incorporate deep learning and neural architecture search for even more sophisticated prediction and heterogeneity detection

7 Conclusion

This paper develops an AI-driven causal inference framework to evaluate the heterogeneous effects of eight major housing policy instruments on severe housing cost burden in New York City. By integrating ensemble machine learning for prediction with triple quasi-experimental designs for causal inference, we find that HSTPA's 2019 rent stabilization expansion reduced severe burden by 6.2 percentage points, while tenant protection ordinances and housing court access reforms demonstrated the largest effects among complementary policies. Significant heterogeneity exists in policy effectiveness across neighborhood characteristics, with stabilization policies being more effective in high-opportunity, high-eviction areas.

Our policy matrix framework demonstrates that coordinated approaches targeting stabilization, protection, and access yield the greatest reductions in housing insecurity. These findings suggest that effective housing policy requires both foundational stabilization measures and complementary protections that address the multidimensional nature of housing affordability challenges in urban settings.

The contrasting results between ERAP and CityFHEPS further highlight that program design, timing, and implementation quality are crucial determinants of policy effectiveness. Emergency assistance programs may require different design features than ongoing housing support programs to achieve their intended goals.

As cities worldwide grapple with increasing housing unaffordability, evidence-based policy design becomes increasingly critical. Our analysis provides a template for evaluating housing policies using AI-enhanced causal inference strategies and highlights the importance of considering both average effects and contextual heterogeneity when designing housing interventions.

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