

SHIFTS IN SHORT-TERM RENTAL HOSTING  
COSTS FOLLOWING REGULATORY CHANGES  
IN NEW YORK CITY

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

Shashwat Chaterji

August 2025

© 2025 Shashwat Chaterji

ALL RIGHTS RESERVED

## ABSTRACT

On September 5, 2023, New York City implemented Local Law 18, or the Short-Term Rental Registration Law. This thesis examines how the opportunity cost of hosting short-term rentals on online marketplaces changed after the enforcement of this law. I develop a structural supply model and estimate daily market-level cost distribution parameters across different categories of Airbnb rentals. For short-term rentals of less than 30 days, the cost distribution means increase sharply at enforcement. Thereafter, costs stabilize at a level above the pre-enforcement average for partial-property listings, but exhibit a gradual decline over time for entire-property listings. For rentals of over 30 days, the seasonal variation in costs remains unchanged. These patterns are consistent with expectations based on the regulation's specific provisions. They characterize the supply-side response to regulation, which can inform future work in modeling short-term rental markets and policy.

## BIOGRAPHICAL SKETCH

Shashwat Chaterji is from Kolkata, India, and grew up in different parts of the country. He received a Bachelor of Engineering degree in Chemical Engineering from the Birla Institute of Technology and Science, Pilani (Goa Campus). During his undergraduate studies, he developed an interest in economics, especially in the field of development economics. He is expected to receive a Master of Science degree in Applied Economics and Management from Cornell University in August 2025.

Previously, he has worked as an archival researcher, tracing the evolution of grazing regulation in British India. He was also a research consultant at Innovations for Poverty Action, Bangladesh, where he supported a Covid-19 impact survey and a randomized evaluation of remote education. As a Teach For India fellow, he taught middle and junior high school students at a low-income private school for two years.

Dedicated to my parents and grandparents.

## ACKNOWLEDGEMENTS

I would like to thank Dr. Lauri Kytömaa for his time and support throughout the past year. This thesis grew out of my work as his research assistant, and the practical experience was a key aspect of my learning at Cornell. I truly appreciate his thoughtful and patient guidance as I developed this thesis, especially since I was previously unfamiliar with the topic and methods involved. I am grateful to Dr. Calum Turvey for his detailed feedback over several iterations of this work, and for the advice and support throughout my academic journey. I would also like to thank the course faculty who ensured that my time here was full of incredible learning experiences.

My path to this master's program was long and winding, and I am deeply thankful to my family and friends for their support along the way. I very much appreciate my friends in the AEM master's cohort, my constant partners in brainstorming ideas, fixing misconceptions, powering through problem sets, and enduring the challenges of graduate school. To my friends in Ithaca, thank you for all the adventures and for making the place feel like home.

## TABLE OF CONTENTS

Biographical Sketch . . . . .	iii
Dedication . . . . .	iv
Acknowledgements . . . . .	v
Table of Contents . . . . .	vi
List of Tables . . . . .	vii
List of Figures . . . . .	viii
<b>1 Introduction</b>	<b>1</b>
<b>2 Background and Literature Review</b>	<b>4</b>
2.1 The Short-term Rentals Debate . . . . .	4
2.1.1 Welfare Impact and Benefits . . . . .	4
2.1.2 Housing Reallocation and Negative Externalities . . . . .	6
2.1.3 Regulating Peer-hosted STRs . . . . .	8
2.2 Regulation in New York City . . . . .	10
2.2.1 Evolution of STR Governance . . . . .	11
2.2.2 Requirements after Local Law 18 . . . . .	13
2.3 Research Question . . . . .	14
<b>3 Theoretical Model</b>	<b>17</b>
3.1 Peer-Host Supply Function . . . . .	17
3.2 Comparative Statics . . . . .	19
<b>4 Data</b>	<b>21</b>
<b>5 Estimation Strategy</b>	<b>26</b>
<b>6 Results</b>	<b>28</b>
6.1 Short-term Rentals . . . . .	29
6.2 Medium-term rentals . . . . .	33
<b>7 Conclusion</b>	<b>36</b>
<b>A Flexible Variance Specification</b>	<b>38</b>
<b>B Non-Exiters</b>	<b>41</b>
<b>C Instrument Validity</b>	<b>44</b>
<b>Bibliography</b>	<b>49</b>

## LIST OF TABLES

2.1	Key requirements under New York City’s Short-Term Rental Registration Law (Local Law 18) . . . . .	14
4.1	Descriptions of raw datasets . . . . .	21
6.1	Coefficient estimates for short-term rentals. . . . .	30
6.2	Cost parameters for short-term rentals. . . . .	30
6.3	Coefficient estimates for medium-term rentals. . . . .	33
6.4	Cost parameters for medium-term rentals. . . . .	34
A.1	Estimates for STRs using the flexible variance specification. . . . .	39
A.2	Cost parameters for STRs using the flexible variance specification. . . . .	40
B.1	Coefficient estimates for short-term rentals that do not exit at enforcement. . . . .	41
B.2	Cost parameters for short-term rentals that do not exit at enforcement. . . . .	42
C.1	First-Stage OLS Estimates. . . . .	45

## LIST OF FIGURES

2.1	83.5% decline in STR listings at regulation enforcement. . . . .	15
3.1	Comparative statics: Increasing mean-shift from regulation . . . .	19
3.2	Comparative statics: Increasing available supply. . . . .	20
3.3	Comparative statics: Increasing hosting-cost standard deviation.	20
4.1	Assumption: A unit is considered booked if it was seen as avail- able but ultimately becomes unavailable. . . . .	22
4.2	Daily NYC availabilities and bookings, as seen in our data. . . .	23
4.3	Weekly averages of the dependent variable and market price. . .	25
6.1	Estimated peer-host cost distribution means for short-term rentals.	31
6.2	Linear trends in cost distribution means for short-term rentals. .	32
6.3	Estimated peer-host cost distribution means for medium-term rentals. . . . .	35
A.1	Estimated peer-host cost distribution means through a specifica- tion that allows variance to change at enforcement. . . . .	40
B.1	Estimated peer-host cost distribution means for short-term rentals that do not exit the market at enforcement. . . . .	43
C.1	First stage scatter-plots. . . . .	46

## CHAPTER 1

### INTRODUCTION

On September 5, 2023, New York City (NYC) began enforcing its Short-Term Rental Registration Law. This law marked the culmination of a series of policy efforts to regulate short-term rentals (STRs), defined locally as housing rentals of fewer than 30 consecutive days. By requiring rental hosts to register their listings with the city, the law aims to ensure compliance with all applicable STR regulations. The law also places the burden of compliance on both hosts and on-line platforms, such as Airbnb and Vrbo, by imposing penalties on both parties if unregistered STRs are found listed on these websites. The impact after enforcement was immediate and substantial, resulting in a sharp decline in STRs listed on Airbnb (83.5% as seen in our data) and prompting heavy backlash from both online marketplace providers and affected hosts.

Tension between STR platforms and hosts, and local governments and urban communities, is neither new nor unique to NYC. Since its inception in 2008, Airbnb has expanded globally, growing to list more rooms than any hotel group in the world<sup>1</sup>. The growth of peer-hosted STRs has been shown to stimulate economic activity through increased tourism, while generating substantial gains for local businesses and hosts. At the same time, it has raised concerns about the reallocation of long-term housing, the commercialization of residential neighborhoods, the displacement of incumbent urban populations, and safety risks. Earlier this year, protests broke out over these concerns across Spain<sup>2</sup>.

City governments have grappled with balancing resident concerns and the

---

<sup>1</sup><https://news.airbnb.com/en-au/airbnb-global-growing/>

<sup>2</sup><https://www.reuters.com/world/europe/protesters-rally-across-spain-against-housi>

lawful operation of peer-hosted short-term rentals. Efforts to regulate STRs have frequently led to protracted legal disputes <sup>34</sup>. The hotel industry also weighs in, characterizing Airbnb listings as unregulated hotels operating outside the bounds of transient lodging law<sup>5</sup>. Even once regulation is in place, enforcement is difficult since authorities must monitor a constantly shifting pool of individual hosts, making it challenging to track listings and ensure ongoing compliance. Best practices for designing regulatory frameworks, so that the interests of all stakeholders are equitably considered, remain to be established.

After a decade-long effort to regulate STRs and ensure their adherence to existing laws, NYC's new law seeks to enforce compliance preemptively by requiring all STRs to be registered before they can be advertised or listed on peer-to-peer platforms. In our data, 83.5% of STRs are observed to be immediately de-listed following its enforcement (Figure 2.1). To characterize the impact of this law, this thesis seeks to understand how the opportunity costs for hosting STRs evolved in its aftermath. To do so, I adapt the approach developed by [Farronato and Fradkin, 2022] in their analysis of Airbnb growth's welfare effects. Hosting behavior is modeled using a set of assumptions, and a market-level supply function is derived accordingly. I then estimate this function using my data to recover the parameters of the underlying cost distribution. This enables the tracking of hosting costs over time, providing a direct basis for quantifying changes following regulation. The results illustrate the impact of regulation on Airbnb hosts and the corresponding supply-side response.

I find that the cost distribution mean for STRs increases substantially fol-

---

<sup>3</sup><https://apnews.com/article/spain-airbnb-housing-tourism-36f8bf81c5a9d09a980fdd57>

<sup>4</sup><https://apnews.com/article/airbnb-lawsuit-new-orleans-f72e801422838e5686e54c2ac7>

<sup>5</sup><https://www.nytimes.com/2017/04/16/technology/inside-the-hotel-industrys-plan-to-combat-airbnb.html>

lowing the policy's implementation. However, the post-enforcement dynamics differ by listing type. For partial-unit STRs, the cost mean rises sharply and then stabilizes at a level above the pre-enforcement baseline. Full-unit STRs also experience an initial spike, but their cost mean gradually declines over the remainder of the analysis period. In contrast, medium-term rentals (MTRs) , or rentals of 30 days or more which are exempt from regulation [Kytömaa, 2019], show no noticeable change in cost means. I use these results to draw inferences about the nature of the regulation's effects, comparing them against the specific requirements imposed on hosts.

The rest of this thesis is organised as follows: chapter 2 provides further background on this topic and introduces the relevant literature, chapter 3 sets up the theoretical framework, chapter 4 outlines our data and key variables of interest, chapter 5 discusses the estimation strategy, chapter 6 presents the results, and chapter 7 concludes. The appendices include two extensions of the main analysis and a discussion of the instruments used for estimation.

## CHAPTER 2

### BACKGROUND AND LITERATURE REVIEW

#### **2.1 The Short-term Rentals Debate**

Drawing on academic studies, I provide a broad overview of the economic and policy implications of peer-to-peer marketplaces entering local housing markets. I then review the regulatory approaches adopted across jurisdictions and outline assessments of their effectiveness.

##### **2.1.1 Welfare Impact and Benefits**

Peer-to-peer platforms (such as Airbnb and Vrbo) lower entry barriers and reduce marginal costs for small-scale suppliers, enabling the entry of ‘peer’ providers. These providers typically supply their owned but unutilized assets to the market, and do so with much greater flexibility than traditional suppliers. Their supply elasticity allows them to respond rapidly to demand fluctuations and price changes, enabling direct competition with large-scale incumbent firms whose dedicated supply tends to be constrained during peak periods and underused when demand is low.

This feature of peer-entry is illustrated by [Farronato and Fradkin, 2022], who characterize welfare changes in the U.S. transit accommodation industry after the emergence of Airbnb. They estimate a \$305 million increase in consumer surplus, driven by lower hotel prices and an expanded choice set, and \$112 million in host surplus. These gains come at the expense of hotel revenues

(up to 1.6%) and variable profits (up to 2.8%). In particular, they find that the welfare effects are concentrated when hotel capacity is constrained, demonstrating the benefits of peer-supply flexibility. Additionally, they find that Airbnb is market-expanding, providing lodging options to guests who would not have chosen to stay in a hotel otherwise. Overall, they find that Airbnb increases total welfare among hosts, guests, and hotels. [Schaefer and Tran, 2020] extend these results to account for localized competition within the city districts of Paris and reach similar conclusions. In Austin, Texas, [Zervas et al., 2017] estimate that Airbnb supply reduces hotel revenues by 8–10%, with lower-priced hotels and those not catering to business travelers being most affected. They continue to find this impact being driven by more competitive hotel pricing, with effects particularly pronounced during periods of peak demand.

Other studies show that the expansion of Airbnb generates positive spillovers in local economies, which may be attributed to increased tourist inflows and spending [Fang et al., 2016, Kim et al., 2025]. Despite a loss in hotel revenues, [Dogru et al., 2020] find that Airbnb expansion is associated with increased hotel employment. [Hidalgo et al., 2022] and [Basuroy et al., 2020] find positive effects of Airbnb activity on the restaurant industry. The latter additionally show that this effect is stronger in the less-commercial areas of cities in Texas, which are also the target of local regulatory restrictions. Finally, [Lin et al., 2022] show that home-sharing relaxes the liquidity constraints of hosts, thereby reducing mortgage (3.99%) and auto-loan (2.68%) delinquencies. They also find evidence that these effects are weakened, and in some cases offset, as governments start regulating short-term rentals.

## 2.1.2 Housing Reallocation and Negative Externalities

For all its perceived benefits, the widespread proliferation of peer-hosted short-term rentals has raised growing concerns about the broader impacts on urban housing markets and neighbourhood dynamics. This unease has sparked a highly contested debate involving local residents, peer hosts, regulators, political actors, the hotel industry, and the technology firms that operate these platforms.

A primary concern is the reallocation of housing from long-term residential use to short-term rentals, especially in cities where the housing stock is already under significant pressure. [Calder-Wang, 2021] analyses the welfare and distributional impact of Airbnb on renters in supply-constrained NYC. Reallocation of housing to STR-usage results in increased rents across all housing units, aggregating to a \$2.7 billion transfer from renters to property owners. Some of these losses are offset by a welfare gain of \$0.3 billion among hosts with a low cost of home-sharing, resulting in a net renter welfare loss of \$2.4 billion. Additionally, heterogeneous effects estimated by this paper show that these losses are primarily borne by renters who are higher income, more educated, and white, since their housing preferences are similar to those of short-term visitors. Consistent with [Farronato and Fradkin, 2022], Airbnb is still found to increase total welfare, but the median NYC household is made worse off. In a similar study, [Li and Srinivasan, 2019] find that STR expansion is driven both by reallocation and new entrants to the rental market. However, they find that the reduction in rental supply is greatest among affordable units and more pronounced in cities with higher levels of Airbnb activity, lending credibility to housing concerns.

Studies have shown that Airbnb growth is associated with rising rents and

housing prices across geographies, including in Boston [Horn and Merante, 2017], Barcelona [Garcia-López et al., 2020], Amsterdam [Almagro and Domínguez-Iino, 2025], and Portugal [Franco and Santos, 2021]. Using a web-scraped dataset of listings across the U.S., [Barron et al., 2020] reach similar conclusions. They further show that the effect is more pronounced in zip codes with lower rates of owner occupancy. Multi-property hosts who operate their non-primary residences as short-term rentals are often characterized as ‘commercial’ hosts. They are a central focus of criticism directed at Airbnb and are frequently targeted by regulatory interventions.

Increased short-term rental activity also changes local neighbourhoods, leaving some residents worse off. [Almagro and Domínguez-Iino, 2025] consider the endogeneity of local amenities to resident welfare. As neighborhoods adapt to increased tourism, younger and higher-income residents may benefit from shifts in local amenities, since their preferences often align with those of visitors. This can offset the welfare losses they experience from rising rents. However, these shifts tend to further amplify the losses of older and lower-income residents. Within the planning literature, the commercialization of short-term rentals and resulting stimulation of neighborhood investment are characterized as forms of gentrification, which can increase rent disparities within a city and lead to the displacement of incumbent lower-income residents [Xu and Xu, 2021, Wachsmuth and Weisler, 2018].

Short-term rentals can fall outside existing land-use restrictions and often draw tourists into residential zones, prompting complaints from residents about noise, traffic, parking shortages, waste management, and other disruptions [Gurran and Phibbs, 2017]. They have also been linked to increases in

crime [Han et al., 2021, Maldonado-Guzmán, 2022]. Using a randomized experiment, [Cui et al., 2020] find evidence of racial discrimination by hosts. Finally, the legitimacy of Airbnb-listed properties in many regions has come under legal scrutiny, since they may technically be illegal under local safety, zoning, and tax laws, and other pre-existing regulations. [Guttentag, 2015, Schneiderman, 2014].

### 2.1.3 Regulating Peer-hosted STRs

In light of the questions of legitimacy and fairness posed by peer-hosted STRs, cities across the world are implementing policies to regulate them. Local governments have taken different approaches in doing so and have seen varying degrees of success in meeting their stated goals. In general, the regulatory response to STRs can be grouped into three categories based on their restrictiveness [Nieuwland and van Melik, 2020, Jefferson-Jones, 2015]:

- *Laissez-faire* or with minimal requirements such as:
  - Meeting basic safety and transparency standards.
  - Paying taxes.
- A combination of measures intended to curb unchecked STR growth, which is the most common approach:
  - Permit requirements and limits on the number of STRs.
  - Limits on guests per property and the number of nights it may be rented out each year.
  - STR permitted in primary residence only, in some cases requiring

host presence during the rental period.

- Certain housing types prohibited from being listed as STRs.
- Data sharing requirements and disclosures to regulators.
- Prohibition in certain blocks or throughout a city.

These measures are typically justified on grounds of preserving the residential character of neighbourhoods, protecting housing stock, ensuring safety, enforcing zoning laws, and maintaining tax fairness. While some cities prioritize one over the others, most regulations cite a combination of these concerns [Schneiderman, 2014, Jefferson-Jones, 2015].

Enforcement, however, has proven difficult. One reason is that regulation targets individual suppliers in peer-to-peer marketplaces rather than the platforms themselves. In a dynamic market like Airbnb, where listings are constantly changing, tracking hosts and ensuring compliance is a difficult task [Nieuwland and van Melik, 2020]. Sweeping ordinances can also have unintended consequences, an argument cited by peer-hosts and Airbnb in resisting enforcement, resulting in numerous lawsuits (cite websites). The following paragraph briefly summarizes studies on STR regulation in various cities.

[Jin et al., 2024] evaluate Chicago's 2016 legislation, which they describe as a 'middle-ground' approach in terms of restrictiveness, and find a 16.4% decline in the total number of listings post enforcement. Further, they find that while individual hosts reduced activity immediately after the legislation was enacted, this effect is only seen for multi-property ('professional') hosts once STR platforms start sharing data with regulators. In New Orleans, [Valentin, 2021] finds that ordinances decreased STR activity as intended, but also reduced property values, suggesting that potential STR usage might be a factor in the decision

to purchase a house. This study also finds a spillover to adjacent areas, where STR usage increased post-regulation. [Koster et al., 2021] show that the Home-Sharing Ordinances of Los Angeles County reduced Airbnb listings by 50%, and house prices and rents by 2% on average. To improve its relationship with some city governments (including NYC), Airbnb self-regulated by allowing each host to list a single address on the platform. [Chen et al., 2022] find that this policy reduced rents and property values, and this can be attributed to an increase in residential housing supply. Lastly, [Jia and Wagman, 2020] analyze the impact of two events in NYC that were precursors to the full-scale enforcement which is the focus of this thesis. In November 2015, the city's mayor made a monetary commitment to pursue STR listings that were illegal under New York State's Multiple Dwelling Law. A year later, the state amended this law to prohibit advertising such listings. The study finds that these events reduced the number of Airbnb listings while increasing prices and occupancy rates among the remaining ones, suggesting that illegal listings may have been successfully targeted.

## **2.2 Regulation in New York City**

Next, I examine New York City's experience with STR regulation. I outline major policy developments leading up to the enforcement of the STR registration law and detail the key requirements following its implementation.

## 2.2.1 Evolution of STR Governance

The enforcement of NYC's Local Law 18, which is the topic of this thesis, marked the culmination of a regulatory framework that was developed for more than a decade. This section provides an overview of the proceedings that led to this law, drawing on accounts by [Wachsmuth and Weisler, 2018], [von Briel and Dolnicar, 2021], and media coverage<sup>1, 2</sup>.

Short-term rentals were unregulated in 2008, when Airbnb started operating in NYC. In 2010 and 2011, New York State amended its longstanding Multiple-Dwelling Law (MDL), prohibiting STRs in certain types of housing (categorised as class A) unless the permanent resident is also present during the rental period. Under the suspicion that many listings were non-compliant with existing laws, the New York State Attorney General issued a subpoena to Airbnb in 2013, demanding the records of hosts operating in the state. This resulted in a protracted legal exchange, but Airbnb eventually provided the records. The Attorney General's office used this data to prepare a report on STR activity in NYC. Based on the review period from January 2010 to June 2014, the findings were as follows [Schneiderman, 2014]:

1. STR bookings increased more than tenfold, with associated revenue nearly doubling each year.
2. 72% of listings appeared to be in violation of laws prohibiting STRs.
3. Only 6% of hosts listed more than two unique units on the platform. However, these 'commercial' hosts accounted for 36% of total bookings and

---

<sup>1</sup><https://skift.com/2023/08/31/airbnb-vs-new-york-city-a-skift-timeline/>

<sup>2</sup><https://www.nytimes.com/2023/09/05/nyregion/airbnb-regulations-nyc-housing.html>

received 37% of the total host revenue.

4. In 2013, nearly 2,000 units were booked as STRs for at least half the year (182 days), effectively removing them from the long-term housing market.
5. The share of revenue generated by such listings has been growing.
6. Taxes potentially applicable to STRs are unpaid, resulting in an estimated liability of \$33 million.

In the following years, regulatory and enforcement efforts intensified, as did legal disputes between the city and STR platforms. Towards the end of 2015, the mayor made a \$10 million commitment to pursue illegal STRs. In October 2016, New York State passed an additional amendment to the MDL, making it illegal to advertise rentals of less than 30 days. Airbnb filed a lawsuit contesting the change, but soon withdrew it after reaching an agreement that penalties would apply to hosts rather than the platform. These measures initially reduced Airbnb listings significantly, but the numbers gradually recovered over time. In July 2018, New York State introduced another change to the MDL, mandating STR platforms to share data on hosts and transactions. This bill was initially blocked by a federal judge after opposition from the platforms. Two years later, Airbnb reached a data-sharing agreement with the NYC government.

To further strengthen enforcement, New York City adopted Local Law 18 in January 2022<sup>3</sup>. The law required short-term rental hosts to register with the city and prohibited platforms from processing transactions for unregistered hosts. Airbnb filed another lawsuit against the city, calling the law a 'de-facto' ban on STRs<sup>4</sup>. The case was ultimately dismissed by the New York Supreme Court,

---

<sup>3</sup><https://www.nyc.gov/site/specialexecutive/registration-law/registration.page>

<sup>4</sup><https://news.airbnb.com/an-update-about-our-community-in-new-york-city/>

and enforcement of the new law began on September 5, 2023.

## 2.2.2 Requirements after Local Law 18

New York City began enforcing Local Law 18, or the Short-Term Rental Registration Law, on 5th September 2023. As the name suggests, the law requires STR hosts to register with the Mayor’s Office of Special Enforcement (OSE), and prohibits booking platforms from processing transactions for unregistered STRs. Requiring registration and city approval is intended to enhance compliance with pre-existing rules under the city’s Administrative Code<sup>5</sup>, the state’s Multiple Dwelling Law<sup>6</sup>, and other laws. Table 2.1 outlines the key restrictions and requirements set out under this regulation.

Hosts have been reported to find these new rules burdensome and inflexible<sup>7</sup>, given that they must now navigate complex legal requirements and potentially risk losing income from short-term rentals. Conditions such as mandatory host presence and the need for all occupants to have full access to the dwelling have been criticized as excessively stringent. Nevertheless, enforcement of the new law led to an immediate and sharp decline in STR listings, with many units subsequently re-listed as MTRs. Figure 2.1 illustrates this trend using our data.

---

<sup>5</sup><https://codelibrary.amlegal.com/codes/newyorkcity/latest/NYAdmin/0-0-0-48092>

<sup>6</sup><https://www.nyc.gov/assets/buildings/pdf/MultipleDwellingLaw.pdf>

<sup>7</sup><https://chicagopolicyreview.org/2024/01/31/behind-nycs-tightening-restrictions-o>

<b>Feature</b>	<b>Description</b>
STR definition	Rental of fewer than 30 consecutive days.
Registration	Required. Non-refundable application fee of \$145.
Host presence	Host must reside in the unit for the entire STR duration.
Unit type	Entire apartments and homes prohibited from STR use.
Ownership	Both owners and tenants can host STRs.
Guest limit	Up to two per household.
Access	All residents (including guests) must have access to all parts of the dwelling unit. Internal doors cannot have key locks.
Liability	Owners liable for illegal STRs, even if hosted by tenants.
Platforms	Must ensure that non-exempt STRs are registered.
Reporting	Platforms must report all STR transactions processed.
Exemptions	'Class B' multiple dwellings, which are approved for short-term occupancy, are exempt from registration.

Table 2.1: Key requirements under New York City's Short-Term Rental Registration Law (Local Law 18)

### 2.3 Research Question

As section 2.1 demonstrates, there are credible arguments on both sides of the short-term rentals debate. For regulation to be both effective and fair, it should address the needs of permanent city residents while minimizing unnecessary collateral effects on those who gain from STRs. In the context of NYC, the primary aim of tightening regulation was to address the city's ongoing housing crisis and reduce disruptions to local communities from rising tourist activity. In doing so, however, policymakers also risk stifling the short-term rental market by making it difficult for hosts to offer legal and non-disruptive rentals within their own homes.

By characterizing changes in the opportunity costs of hosting, this thesis seeks to assess the impact of NYC's Local Law 18 on different types of tran-

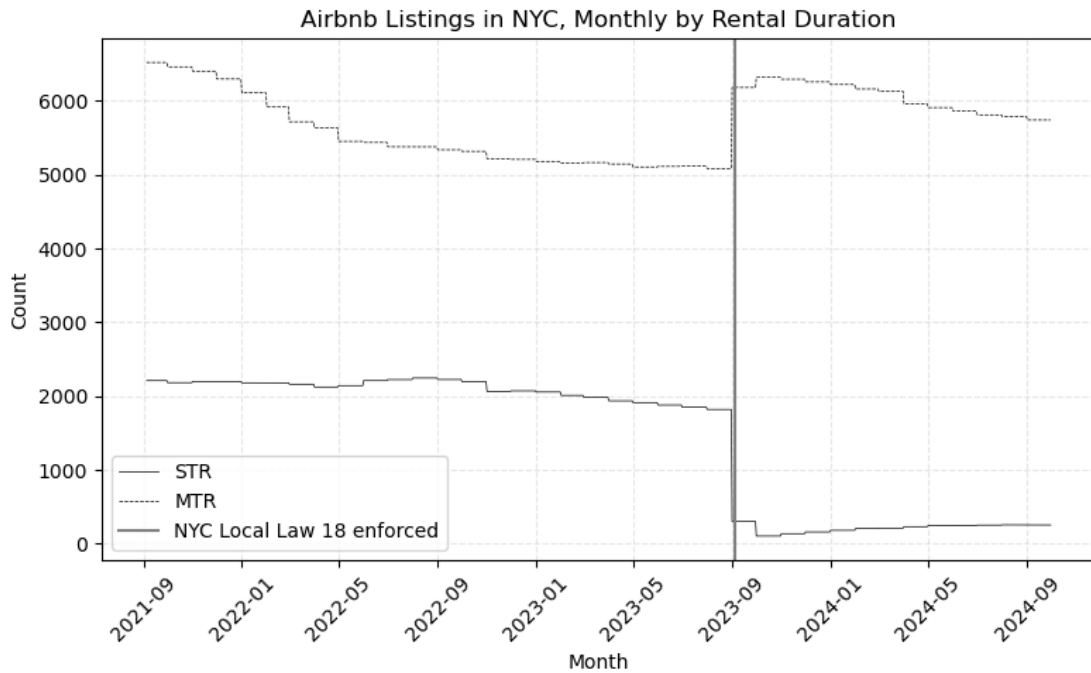


Figure 2.1: 83.5% decline in STR listings at regulation enforcement.

sient rentals. Ideally, hosts who list entire housing units as STRs should face the largest cost increases, since this category is effectively prohibited under the new rules. However, given that strict requirements are imposed on all STR hosts, even those renting out part of their houses are likely to experience higher costs. Since the requirements apply only to STRs, hosts supplying stays longer than 30 days as MTRs should not face any substantial change in costs, although increased MTR supply from STR switchers may alter the market equilibrium.

Positioned within the broader discourse on STR expansion, the thesis contributes to the literature on regulation [Jin et al., 2024, Valentin, 2021, Jia and Wagman, 2020]. Given the relatively recent implementation of Local Law 18, to my knowledge [Voltes-Dorta, 2024] is the only other study that examines its consequences. Although prior STR papers [Calder-Wang, 2021,

Li and Srinivasan, 2019] also use structural methods, to the best of my knowledge, this is the first to directly evaluate how latent hosting costs are affected by regulation. The corresponding results therefore illustrate the response of hosts to regulation and, along with further assumptions on market competitiveness and the parametric form of the cost distribution, can be used to characterize the elasticity of STR supply. Together, the approach and results suggest a methodological framework that can inform future efforts to model peer-hosted STR markets and associated policy interventions.

CHAPTER 3  
THEORETICAL MODEL

### 3.1 Peer-Host Supply Function

To model host behavior and ultimately quantify hosting costs, I modify the peer-host supply function presented in [Farronato and Fradkin, 2022], adding a simple extension. In this model, the NYC Airbnb market is defined as clearing daily. Therefore, each day is considered a separate market, and the terms ‘market’, ‘day’, and ‘time-period’ are analogous in the context of this thesis.

A host’s decision to supply their available listing(s) is based on two assumptions. First, we assume that for each STR listing, hosts draw marginal costs from a market-specific cost distribution. These draws are independent and identically distributed across listings. The marginal cost of supplying listing  $n$  in market  $t$  is therefore a random variable given by,

$$C_{n,t} \stackrel{i.i.d.}{\sim} \mathcal{F}(\theta) \tag{3.1}$$

Next, we assume that hosts are price takers and supply their listing as long as its marginal cost is weakly lesser than the market price  $p_t$ . This assumption is justified on the grounds that peer-hosts are typically small-scale suppliers competing with both hotels and other hosts, and thus lack the market power to influence prices. The model is therefore set up such that these marginal costs reflect the opportunity costs of hosts.

With these two assumptions, if  $K_t$  is the total number of listings available to be booked in a market, the market supply at equilibrium  $Q_t$  is based on the

cumulative distribution function (CDF) of  $\mathcal{F}(\theta)$  evaluated at market price  $p_t$ ,

$$Q_t = K_t \cdot Pr(C_{n,t} \leq p_t) \quad (3.2)$$

To arrive at a well-defined supply function, the cost distribution is parameterized as being normal with mean  $\alpha_t$  and variance  $\sigma_t$ . Standardizing  $C_{n,t}$ ,

$$C_{n,t} = \alpha_t + \sigma_t Z_{n,t}, \quad \text{where } Z_{n,t} \sim \mathcal{N}(0, 1)$$

and rewriting in terms of the standard normal CDF  $\Phi(\cdot)$ , we get,

$$\begin{aligned} Q_t &= K_t \cdot Pr(\alpha_t + \sigma_t Z_{n,t} \leq p_t) \\ Q_t &= K_t \cdot Pr\left(Z_{n,t} \leq \frac{p_t - \alpha_t}{\sigma_t}\right) \\ Q_t &= K_t \cdot \Phi\left(\frac{p_t - \alpha_t}{\sigma_t}\right) \end{aligned} \quad (3.3)$$

Finally, I extend the original model by introducing a post-regulation mean shift parameter, arriving at a short-term supply function,

$$Q_t = K_t \cdot \Phi\left(\frac{p_t - (\alpha_t + \mathbf{1}\{t \geq \tau\} \cdot R)}{\sigma_t}\right) \quad (3.4)$$

Where  $R$  is a mean-shift term representing the additional cost from complying with regulation that takes effect at time  $\tau$ .

Since listing availability,  $K_t$ , is exogenous, this short-term model cannot capture cost changes resulting from host entry or exit driven by regulation. Hosts are restricted to making a single decision, whether or not to supply their available listing. A richer two-step model that also allows hosts to decide whether or not to enter an Airbnb market prior to making their supply decision would more completely capture host behavior under regulation.

### 3.2 Comparative Statics

To illustrate how equilibrium prices and quantities respond to changes in the supply function parameters, I present comparative statics for a market with supply defined by Equation 3.4 and a linear demand function,  $Q_t = \alpha - \gamma p_t$ .

In each of the figures below, I plot prices and quantities over seven days, with regulation taking effect on the fourth day. Quantities are represented as the ratio of equilibrium and available supply ( $Q_t/K_t$ ). Figure 3.1 shows equilibrium prices increasing and quantities decreasing as the additional cost from regulation rises, all else held equal. Increasing the available supply (Figure 3.2) increases the supply ratio and decreases prices. Finally, higher cost distribution variances dampen the effect of regulation (Figure 3.3). A greater dispersion in peer-host costs reduces the share of hosts whose marginal costs are pushed above the prevailing market prices once regulation takes effect.

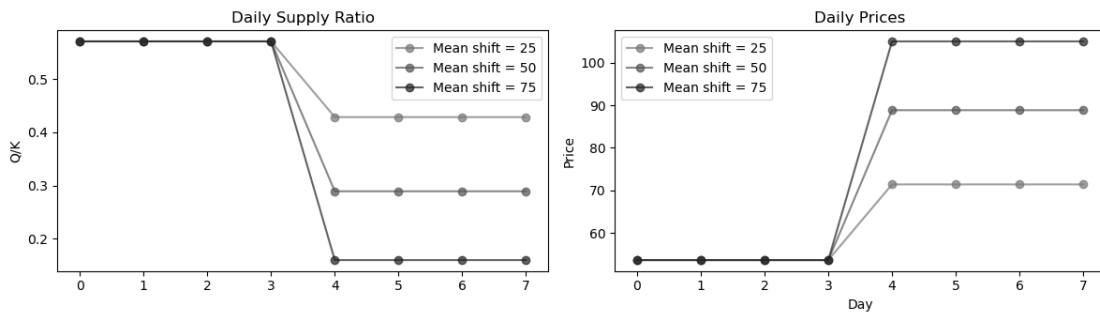


Figure 3.1: Comparative statics: Increasing mean-shift from regulation

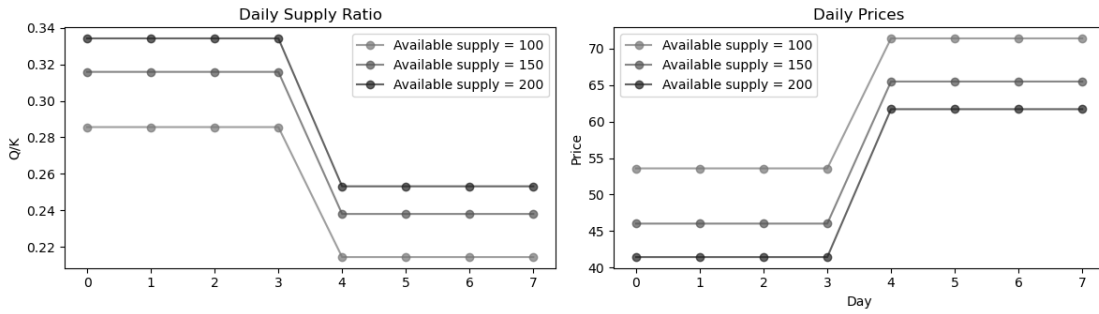


Figure 3.2: Comparative statics: Increasing available supply.

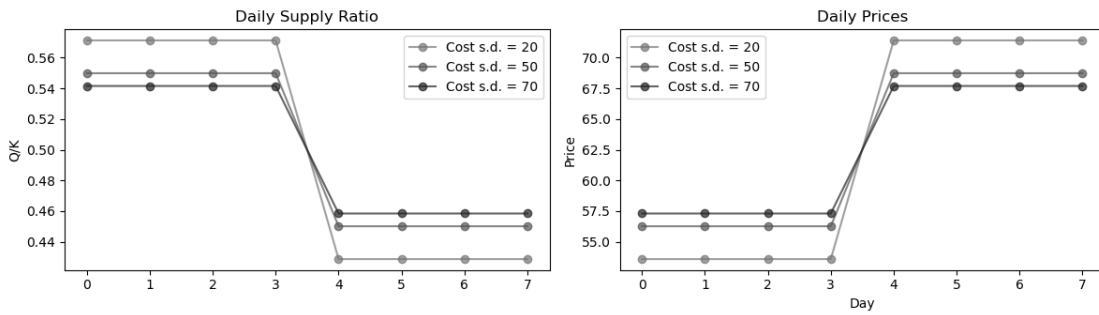


Figure 3.3: Comparative statics: Increasing hosting-cost standard deviation.

## CHAPTER 4

### DATA

Airbnb data for this work is sourced from the Inside Airbnb project <sup>1</sup>. Inside Airbnb is described by its team as being “a mission-driven project that provides data and advocacy about Airbnb’s impact on residential communities.” The team collects, processes, and archives region-specific Airbnb listings data by periodically scraping the platform’s website. The datasets I use were scraped on a monthly basis between September 2021 and September 2024, and fall into the three distinct categories described in Table 4.1. Dictionaries for these datasets are available on the project website <sup>2</sup>.

<b>Dataset</b>	<b>Description</b>
<i>Listings Data</i>	Snapshot of current attributes for each unit listed on Airbnb during the scrape. Includes information on hosts, location, availability, amenities, and reviews. Frequency: Monthly
<i>Calendar Data</i>	Information from each listing’s calendar covering a one-year period starting from the scrape date. Includes information on availability and prices. Frequency: Daily
<i>Reviews Data</i>	Reviews and review information for each listing. Frequency: Cumulative

Table 4.1: Descriptions of raw datasets

All three datasets are combined to construct daily-frequency data that track availabilities, bookings, and prices across rental types. The data processing is based on the code available at the *CleanAirbnb* project <sup>3</sup>. First, units are classified

<sup>1</sup><https://insideairbnb.com/about/>

<sup>2</sup><https://docs.google.com/spreadsheets/d/1iWCNJcSutYqpULSQH1NyGInUvHg2BoUGoNRIGa6Sedit?usp=sharing>

<sup>3</sup><https://github.com/kytola/CleanAirbnb>

as STRs if they are available for bookings of less than 30 days, and as MTRs otherwise. Since the minimum stay duration is only observed when a unit is listed during a scrape, I assume this duration does not change while the unit is unlisted. Next, rentals are marked *full units* if they are described as “Entire home/apt” in the raw data, and partial units if they are called “Private room” or “Shared room”. Hotel listings are dropped, as they are exempt from the regulations this thesis seeks to study.

Scrape Batch				Booking Date
June 2022	July 2022	Aug 2022	Sep 2022	15 Sep 2022
<b>U</b>	<b>A</b>	<b>U</b>	<b>U</b>	Booked
<b>A</b>	<b>U</b>	<b>A</b>	<b>U</b>	Booked
<b>NL</b> →	<b>A</b> →	<b>NL</b> →	<b>U</b>	Booked
<b>U</b>	<b>U</b>	<b>NL</b>	<b>U</b>	Not booked
<b>NL</b>	<b>U</b>	<b>U</b>	<b>A</b>	Not booked

**U** – Unit unavailable      **A** – Unit available      **NL** – Unit not listed/seen

Figure 4.1: Assumption: A unit is considered booked if it was seen as available but ultimately becomes unavailable.

Calendar data, available at a daily frequency, are used to track bookings and availability. The raw data do not differentiate between booked nights and nights when a unit is withheld by the host, treating both as unavailable<sup>4</sup>. However, because the scrapes occur every month and cover a forward-looking period of one year, we can repeatedly observe the status of a unit on a given future date. Using this feature of the data, we assume that a unit-night pair is booked if

<sup>4</sup><https://insideairbnb.com/data-assumptions/>

it was seen as available in a prior scrape but ultimately became unavailable. Figure 4.1 visualizes this method of inferring bookings, which is similar to the process used by [Williams, 2020] to infer airline ticket sales. One caveat of this assumption is that if a booking is canceled by the host but the unit remains unavailable, it would still be marked as booked. This is particularly relevant in the context of regulation, as hosts may retroactively cancel bookings once the policy takes effect. To mitigate this issue, I consider a unit-night as booked only if the unit was also listed during the month in which the booking occurs.

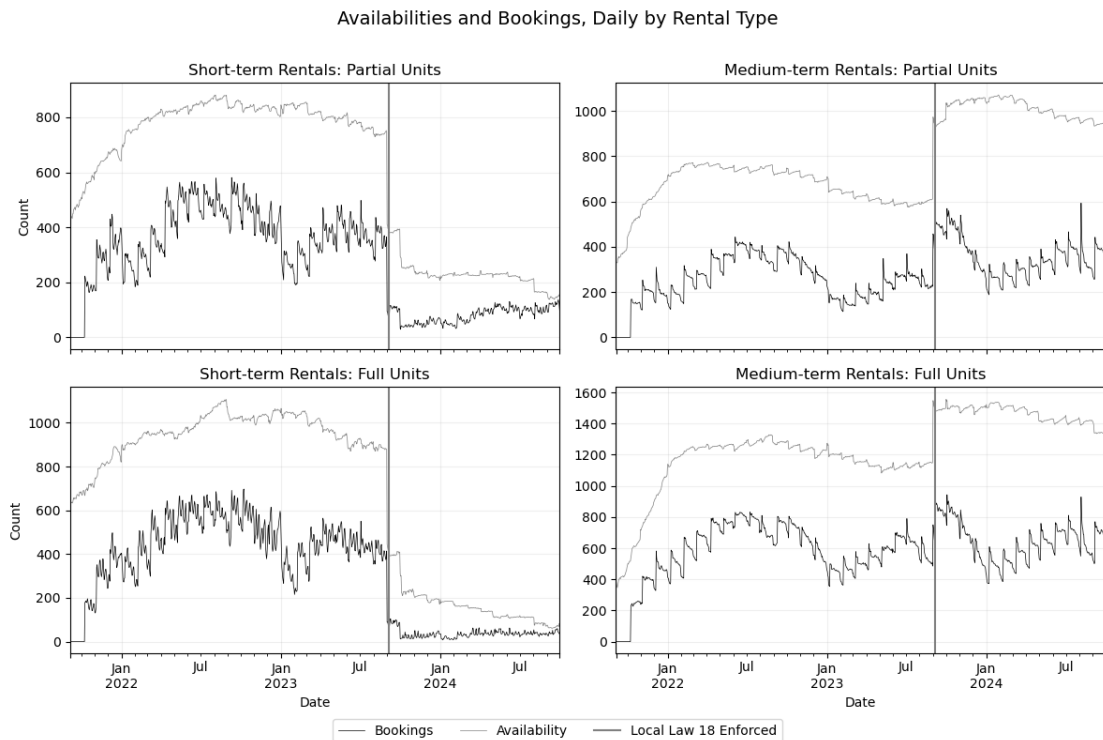


Figure 4.2: Daily NYC availabilities and bookings, as seen in our data.

Review data are also incorporated when inferring availability. A unit is considered available on a given night if it was *ever* seen as such in the calendar data, or received a review within the past 20 days. Since the calendar scrapes provide a forward-looking window, I can infer whether a unit-night is available even if

the unit ultimately gets unlisted for that night. For booked units, if the price is observed during the final availability transition, it is treated as the booking price. Otherwise, the price from the listings data for the booking month is used. The top 0.0001% of prices are excluded, dropping 146 observations and removing unusually high-priced listings. The resulting daily frequency dataset tracks 9,994 unique Airbnb listings, with not more than 2 listings excluded on a given day. Figure 4.2 shows net availabilities and bookings for the four categories of rental units I examine. It should be noted that since scrapes are monthly, the data only captures dynamic changes at a monthly frequency. Zero bookings in the initial days are a byproduct of the data processing method and are excluded from our analysis.

Finally, the model I present in section 3.1 requires the data to be aggregated at the market level, where each day in NYC is considered a separate market. The total number of bookings on a given day is treated as the market supply at equilibrium, while the total availability is thought of as the *potential* supply in the market. The dependent variable is constructed by applying the inverse normal CDF to the ratio of equilibrium supply to potential supply. The market price is the average booking price for that day. Since each rental category is treated as a distinct market, all aggregation is performed separately by rental type. Figure 4.3 shows trends in market prices and the dependent variable across the different categories of rental markets.

$\Phi^{-1}(Q/K)$  and Market Price, Weekly Averages by Rental Type

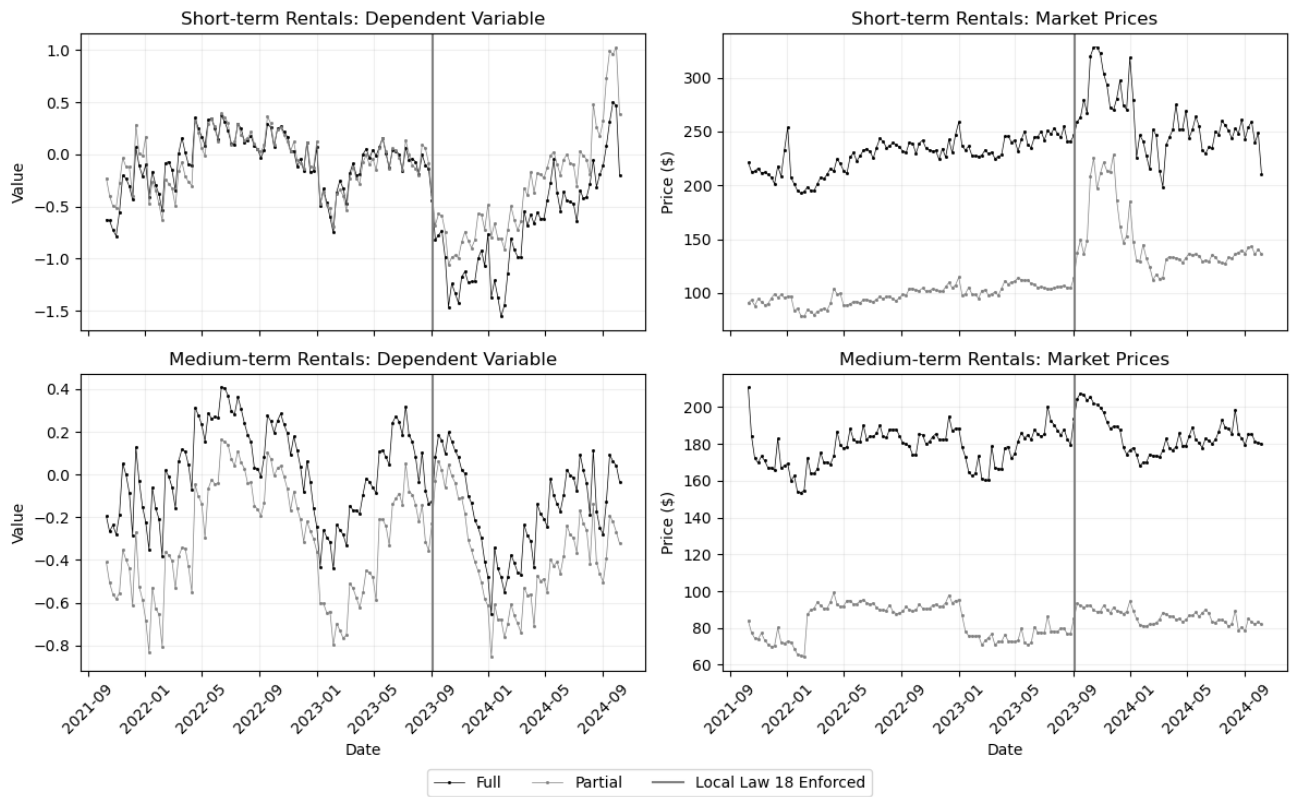


Figure 4.3: Weekly averages of the dependent variable and market price.

CHAPTER 5  
ESTIMATION STRATEGY

I use a two-stage least squares (2SLS) regression to estimate the peer-host supply function from section 3.1, and subsequently recover the cost distribution parameters for different markets. To begin with, I rewrite Equation 3.4 in terms of the inverse normal CDF evaluated at the share of available listings that are supplied on a given day,

$$\Phi^{-1}\left(\frac{Q_t}{K_t}\right) = \frac{p_t}{\sigma_t} - \frac{\alpha_t}{\sigma_t} - \frac{\mathbf{1}\{t \geq \tau\} \cdot R}{\sigma_t} \quad (5.1)$$

I then estimate Equation 5.1 using our data and the following specification,

$$\Phi^{-1}\left(\frac{Q_t}{K_t}\right) = \beta_0 + \lambda_0 t + \beta_p p_t + \beta_{reg} Reg_t + \lambda_{post} (t - \tau) \cdot Reg_t + \eta_{dw} + \gamma_{my} + \varepsilon_t \quad (5.2)$$

Where  $K_t$  is the total number of listings seen available in a given day (market),  $Q_t$  is the total number of bookings, and  $p_t$  is the average booking price across all booked units.  $Reg_t = \mathbf{1}\{t \geq \tau\}$  is an indicator variable for time periods in which regulation, enforced at period  $\tau$ , is in place.  $\lambda_0 t$  represents a linear time trend to capture long-term market changes, while  $\lambda_{post} (t - \tau) \cdot Reg_t$  is an additional trend term that allows the slope of the time trend to change after enforcement.  $\eta_{dw}$  and  $\gamma_{my}$  are day-of-the-week and month-of-the-year fixed effects, respectively.

To address the issue of simultaneity while estimating supply using equilibrium prices and quantities, I instrument for price using Google search interest for the terms ‘*new york hotel*’ and ‘*things to do new york*’. These weekly search trends serve as plausibly exogenous demand shifters, and are transformed using  $\ln(1 + x)$ , linearly de-trended and lagged by five years. Google search trends are used as instruments in the [Farronato and Fradkin, 2022] paper, and else-

where in the related literature [Hidalgo et al., 2022, Barron et al., 2020]. Appendix C discusses their validity in the present context.

Post-estimation, I recover the structural cost parameters of my model. This can be done by comparing Equation 5.2 with Equation 5.1 and noting that,

$$\alpha_t + \mathbf{1}\{t \geq \tau\} \cdot R = - \frac{\beta_0 + \beta_{\text{reg}} \text{Reg}_t + \lambda_0 t + \lambda_{\text{post}}(t - \tau) \cdot \text{Reg}_t + \eta_{dw} + \gamma_{my} + \varepsilon_t}{\beta_p} \quad (5.3)$$

and,

$$\sigma = \frac{1}{\beta_p} \quad (5.4)$$

A limitation of this model is that  $\sigma_t$  is implicitly assumed to be constant across markets. This assumption is also made by the [Farronato and Fradkin, 2022] paper this thesis draws upon. While the original paper is not focused on regulation, it is very likely that the cost distribution variances changed significantly after enforcement. I show results from an alternative model in Appendix A that allows a one-time shift in variance.

Finally, the post-enforcement mean shifts are a function of both  $\beta_{\text{reg}}$  and  $\lambda_{\text{post}}(t - \tau)$ , which allows the effect of the regulation to evolve linearly over time,

$$R_t = - \frac{\beta_{\text{reg}} + \lambda_{\text{post}}(t - \tau)}{\beta_p}$$

Since  $(t - \tau) = 0$  on the day of enforcement ( $\tau$ ), the immediate mean shift associated with the policy change is given by,

$$R_{t=\tau} = - \frac{\beta_{\text{reg}}}{\beta_p} \quad (5.5)$$

I estimate separate regressions for each rental type, treating them as distinct markets.

## CHAPTER 6

### RESULTS

In this section, I present the coefficient estimates from Equation 5.2, as well as the structural cost parameters and cost mean trends calculated post-estimation. I do this separately for the two kinds of rental units (full and partial) and the two rental durations (STRs and MTRs), resulting in four distinct market types.

As mentioned in chapter 3, the short-term supply model I use treats listing availability as exogenous. While it allows hosts to decide whether or not to supply their available listings, the availability itself, driven by host entry and exit, is not modeled. As a result, changes in the observed market-level mean cost reflect a combination of host entry and exit as well as changes in the costs of incumbent hosts, which I am unable to separately identify. Furthermore, if the new regulation did lead to host exit (as is apparent from Figure 4.2), the reported increases in mean costs are likely underestimated, since the cost increases that caused these hosts to exit are not captured. In Appendix B, I present results for STRs after excluding the large number of listings that exit the market at enforcement. Furthermore, while the approach can be used to characterize the evolution of cost distribution means through time, the recovered mean-shift parameter (Equation 5.5) may not *exclusively* represent the causal effect from the policy. Other time-varying factors captured by the error term may be correlated with the timing of enforcement. A better causal estimate can be achieved using a difference-in-differences strategy [Jin et al., 2024, Kytömaa, 2019] or an exogenous instrument for the regulation indicator, but this is left to future work.

## 6.1 Short-term Rentals

The supply coefficients from Equation 5.2 for both types of STR units are shown in Table 6.1. For both full and partial units, the price coefficient is positive and the supply ratio falls after enforcement, as expected. However, the model fits the data very differently for the two unit types. It explains a large part of the variation for full units, with an adjusted R-squared of 0.72. However, the corresponding value is very low for partial units, at 0.002. This is likely due to the difference in price instrument strengths, as can be seen with the F-statistics in Table 6.1. To prevent IV-estimator bias, [Stock and Yogo, 2005] suggest a first-stage f-statistic that is  $> 10$  for a single instrument. While this threshold generally rises with multiple instruments and depends on the specific criterion used (bias or size distortion), I use the rule-of-thumb benchmark of 10 to comment on instrument strength. Conditional on the covariates, my demand-shifter instruments do not show relevance for the partial units STR market, and I discuss this further in Appendix C. Accordingly, the price coefficient for such units is statistically insignificant. Model mis-specification may also pose a concern here, as the specification I use may not be well-suited to capture the substantial changes associated with regulation.

Next, the cost parameter estimates shown in Table 6.2. The *mean pre-enforcement cost* is the average cost distribution mean for days prior to enforcement. This is higher for full units, likely because entire properties are more expensive to host. The *mean-shift at enforcement*, evaluated using Equation 5.5 is the one-time shift in distribution mean on the date the policy takes effect (5 September, 2023). Since the data for September 2023 was scraped on the same day as enforcement, changes that took place right after would only be visible in

<b>Coefficient</b>	<b>Full Units</b>	<b>Partial Units</b>
$\beta_0$ , const.	-2.422** (1.097)	-2.205* (1.141)
$\beta_p$ , price	0.010* (0.006)	0.025 (0.016)
$\beta_{reg}$ , reg. ind.	-1.496*** (0.341)	-2.250* (1.216)
$\lambda_0$ , time trend	-0.001** (0.000)	-0.001* (0.001)
$\lambda_{post}$ , post-reg. trend	0.005*** (0.001)	0.007** (0.003)
Sample Size	1088	1088
First Stage F-statistic	18.14	4.82

Table 6.1: Coefficient estimates for short-term rentals.

Notes: \*\*\* :  $p < 0.01$ , \*\* :  $p < 0.05$ , \* :  $p < 0.1$ . F-stat tests instrument relevance conditional on covariates. Fixed effects excluded from table. Sample size corresponds to the number of days in the estimation period.

the next month’s scrape. Furthermore, since October’s data provides a forward-looking window, host responses between September 5th and 30th are not shown by either scrape. To account for this, I also report the mean hosting costs through the month of October 2023. These values represent 94.64% and 149.1% increases over the corresponding pre-enforcement means for full and partial units.

<b>Cost Parameter</b>	<b>Full Units</b>	<b>Part Units</b>
Mean cost, pre-enforcement	236.05	101.52
Cost std. dev.	99.06	40.75
Mean shift at enforcement	148.21	91.68
Mean cost, Oct 2023	459.46	252.90

Table 6.2: Cost parameters for short-term rentals.

While full units exhibit a larger absolute shift, the relative change is greater for partial units. Regulation places stringent restrictions upon partial units, but prohibits entire properties from being hosted as STRs. Hosts are likely to exit the market if their costs are higher than the present value of their expected stream of

future revenues. Given that all hosts take a common market price, market exits would be purely driven by cost increases. Since the enforcement of a de-facto ban should result in the largest cost spikes, it is likely that a greater proportion of full unit hosts at the right tail of the cost distribution exit permanently at enforcement, resulting in a relatively lower mean increase when compared to partial units.

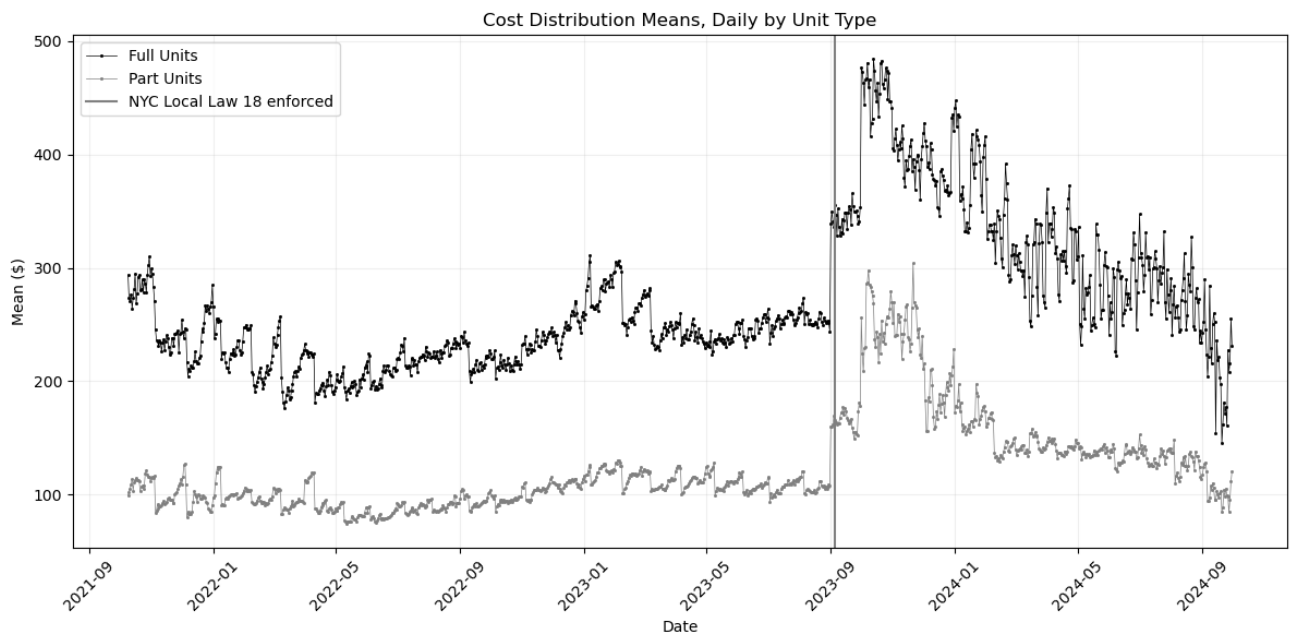


Figure 6.1: Estimated peer-host cost distribution means for short-term rentals.

Figure 6.1 plots the market cost distribution means for both types of STRs, computed using Equation 5.3. Two things stand out about this figure. First, while cost means immediately increase, the largest changes after regulation appear at the start of October. While this is partly because updates after 5th September are only seen in the next month's scrape, it also indicates that the new policy took effect gradually, and not all hosts responded to it immediately at enforcement.

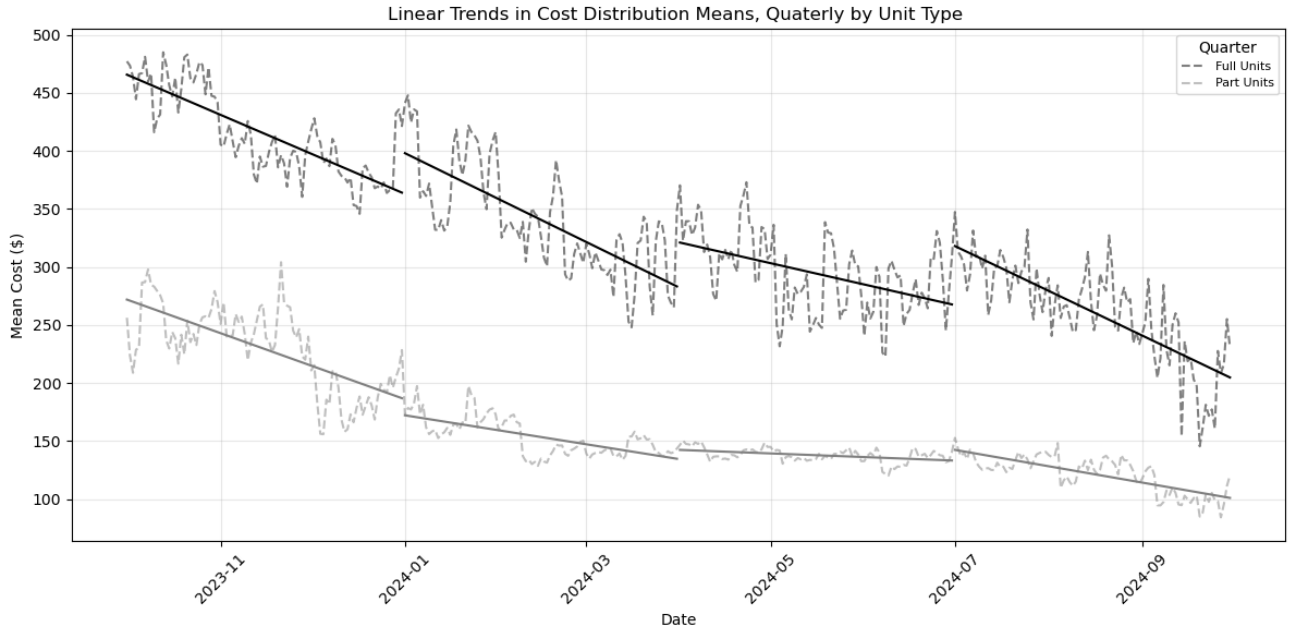


Figure 6.2: Linear trends in cost distribution means for short-term rentals.

Second, the distribution means for the two markets exhibit distinct post-regulation trends. For partial units, the registration process and associated fees impose a one-time administrative and financial burden. After this is complied with, more stringent expectations from hosts continue to pose added costs. The trend for partial units appears to visually reflect this, with mean costs spiking before settling at a level above the pre-enforcement average. Full units, however, are prohibited from STR use. The gradual decline in for such units may reflect hosts with higher costs exiting the market as enforcement intensifies over time. The increased dispersion in market means may also result from a smaller number of listings remaining in the market. Figure 6.2 emphasizes this by plotting the quarterly linear trends after October 2023. The corresponding plot in Figure 4.2 supports this hypothesis by showing a constant decline in the number of available full unit STR listings.

A final point to note is that although Local Law 18 places the burden of compliance on both hosts and platforms, our data show that entire units continue to be booked on Airbnb after the law takes effect. Barring any data errors, this indicates that the new law has not fully succeeded in preventing such properties from being used as STRs one year after enforcement.

## 6.2 Medium-term rentals

Coefficient	Full Units	Partial Units
$\beta_0$ , const.	-0.539 (7.900)	-1.656** (0.728)
$\beta_p$ , price	0.002 (0.049)	0.013 (0.009)
$\beta_{reg}$ , reg. ind.	-0.028 (0.628)	-0.049 (0.112)
$\lambda_0$ , time trend	-0.000 (0.001)	0.000 (0.000)
$\lambda_{post}$ , post-reg. trend	-0.000 (0.003)	-0.001*** (0.000)
Sample Size	1088	1088
First Stage F-statistic	0.35	13.02

Table 6.3: Coefficient estimates for medium-term rentals.

Notes: \*\*\* :  $p < 0.01$ , \*\* :  $p < 0.05$ , \* :  $p < 0.1$ . F-stat tests instrument relevance conditional on covariates. Fixed effects excluded from table. Sample size corresponds to the number of days in the estimation period.

Although rentals over 30 days offer a supply-side alternative for hosts, the new policy is not associated with substantial changes in their hosting costs. Table 6.3 shows the coefficient estimates and instrument relevance for the two MTR markets. The instruments do not show relevance for full unit MTRS, indicated by the low first stage f-statistic. The model explains the variance in the data relatively well for both unit types, with adjusted R-squared values of 0.65

for full units and 0.77 for full units. Supply function price coefficients are positive but statistically insignificant.

<b>Cost Parameter</b>	<b>Full Units</b>	<b>Part Units</b>
Mean cost, pre-enforcement	167.20	105.60
Cost std. dev.	503.12	74.86
Mean shift at enforcement	14.21	3.70
Mean cost, Oct 2023	139.57	92.71

Table 6.4: Cost parameters for medium-term rentals.

The recovered cost parameters in Table 6.4 show the absence of major post-enforcement changes. The mean shifts on the day of enforcement are small compared to the pre-regulation averages, and costs one month later are slightly lower. The particularly high standard deviation for full unit MTRs suggests that this market has high heterogeneity in hosting costs. This might be because such properties represent a distinct market class, and may also feature units meant for long-term residential use. However, this standard deviation value is based on the  $\beta_p$  estimate (Equation 5.4), and the latter is likely biased due to the weak instruments.

Figure 6.3 plots the cost distribution means over time. Since these estimates also rely on the price coefficients, the remarks from the previous paragraph continue to apply. For full units, the means are particularly high on certain days, while being negative on others. Additionally, these means exhibit considerable dispersion over time. Since the unreliable  $\beta_p$  estimate is quite low, it scales up the calculated  $\alpha'_i$  values. Interpreted as is, the negative price means indicate that the mean host on some days would supply their unit regardless of price, and the time dispersion suggests substantial seasonal heterogeneity in hosting costs.

In the context of Local Law 18, the periodic trends in distribution means

remain largely stable after its implementation, suggesting that the policy had minimal impact on the status quo for MTRs. This is expected, since no new requirements were imposed on MTR hosts. Therefore, although the market equilibrium for MTRs may have shifted due to listings re-listing from STRs to MTRs, the underlying hosting costs remain unchanged following the regulation.

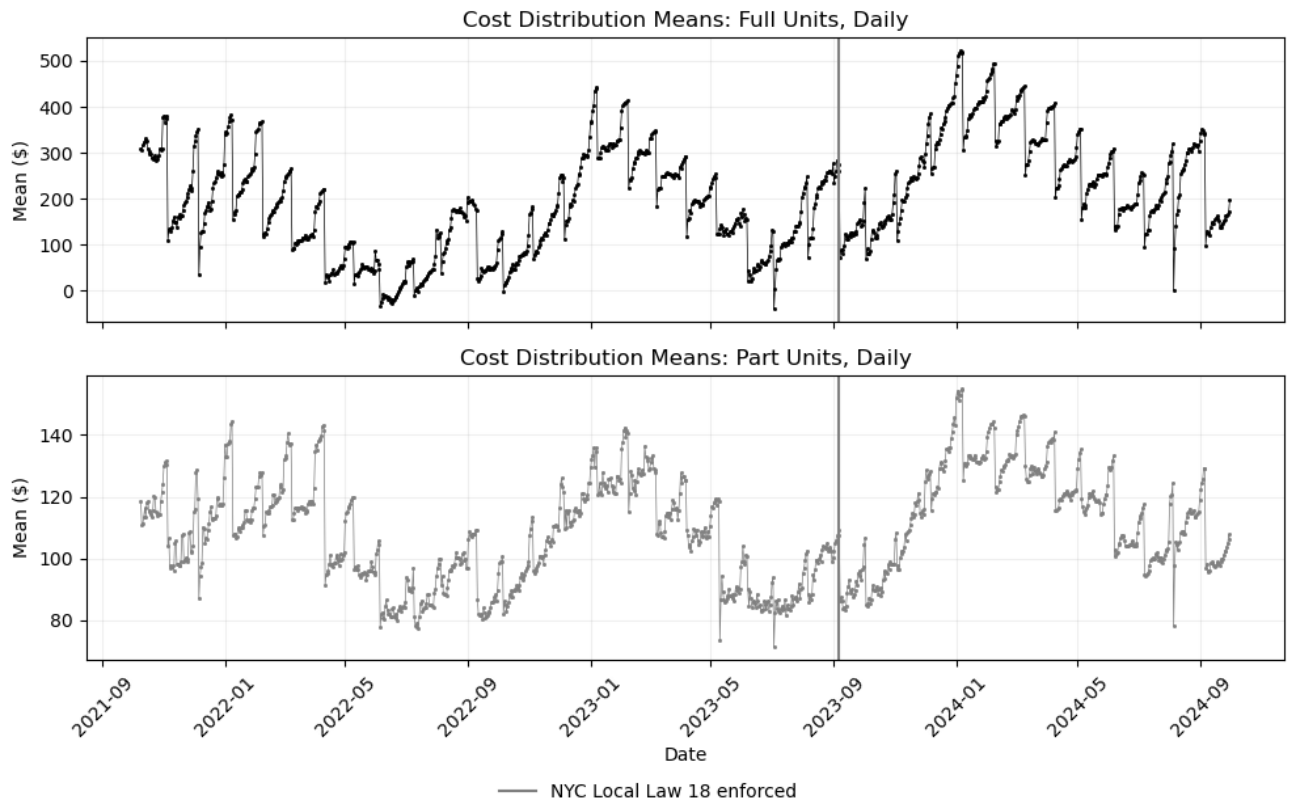


Figure 6.3: Estimated peer-host cost distribution means for medium-term rentals.

## CHAPTER 7

### CONCLUSION

This thesis examines changes to the opportunity costs of hosting various types of Airbnb listings in response to the enforcement of Local Law 18 in NYC. To my knowledge, it is the first to utilize structural modeling to directly assess how regulation affected latent costs. To briefly restate, I began by modeling hosting costs as a latent variable following a normal distribution. I then assumed that hosts drew marginal costs from this distribution, and the draws were independent and identically distributed across hosts and markets. I also assumed that the market cleared daily, with all listings whose hosting costs did not exceed the market price entering supply. I used this framework to derive a supply function that I could estimate using our data, and subsequently recovered the latent cost distribution parameters for each rental category. Finally, I used the recovered parameters to trace changes in hosting costs over time.

For partial properties listed as STRs, I find that mean hosting costs rose sharply at the time of enforcement and then stabilized at a level higher than the pre-enforcement average. Full-property STRs, although prohibited, continue to exist and be booked until the end of our data. These units also experience a large increase in hosting costs at the time of enforcement, which gradually subsides thereafter. MTRs appear to operate largely unchanged after the new policy takes effect. Based on these results, I infer that Local Law 18 successfully imposed more stringent requirements on partial unit STR hosts, as indicated by the higher costs. Although full-unit STRs remain present, I hypothesize based on the post-enforcement cost trend that higher-cost hosts gradually exit the market as enforcement becomes more stringent. Finally, I find no noticeable indication

of collateral impact on MTRs in the aftermath of the law's implementation.

The results depict the supply-side response to NYC's regulation and provide a foundation for further work in modeling STR market policy. Certain constraints limit the scope and validity of this thesis. First, since the data updates at a monthly frequency, I am unable to observe immediate host responses to market shocks. Second, the model treats unit availability as exogenous. Moreover, since each market is estimated separately, the model does not capture potential interactions between options that plausibly act as supply-side substitutes. An alternative approach that allows for host entry/exit and market interactions would offer an interesting extension to this work. Alternate parametric assumptions for the cost distribution and allowing its standard deviation to change over time may lead to more reliable results. Finally, in certain instances, the instruments used for prices are weak, and more relevant demand-shifters could serve as stronger instruments. Each of these considerations offers a potential direction for future work on this project.

APPENDIX A  
FLEXIBLE VARIANCE SPECIFICATION

One limitation of my estimation strategy is that the standard deviation of market cost distributions is implicitly assumed to remain constant across markets. My work is based on the approach used by [Farronato and Fradkin, 2022], who also make the same assumption. The original project, however, is not focused on regulation. In this section, I present results using an alternate strategy that allows the standard deviation to change at enforcement. This is done by introducing an interaction term between the price and regulation indicator variables,

$$\Phi^{-1}\left(\frac{Q_t}{K_t}\right) = \beta_0 + \beta_p p_t + \beta_{\text{reg}} \text{Reg}_t + \beta_{\text{p}\times\text{reg}} (p_t \times \text{Reg}_t) + \lambda_0 t + \lambda_{\text{post}} (t - \tau) + \eta_{dw} + \gamma_{my} + \varepsilon_t \quad (\text{A.1})$$

As with the earlier model, I estimate this specification using a 2SLS regression with demand shifters as instruments for price. I create two additional instruments by interacting the search trends with the regulation indicator variable. Post-estimation, parameters are recovered using the following equations,

$$\alpha_t = - \frac{\beta_0 + \beta_p p_t + \beta_{\text{reg}} \text{Reg}_t + \beta_{\text{p}\times\text{reg}} (p_t \times \text{Reg}_t) + \lambda_0 t + \lambda_{\text{post}} (t - \tau) + \eta_{dw} + \gamma_{my} + \varepsilon_t}{\beta_p + \beta_{\text{p}\times\text{reg}} \text{Reg}_t} \quad (\text{A.2})$$

and,

$$\sigma_t = \frac{1}{\beta_p + \beta_{\text{p}\times\text{reg}} \text{Reg}_t}$$

Which allows the value of  $\sigma_t$  to change once at  $t = \tau$ .

On the day of enforcement,  $t = \tau$ , the immediate shift in mean cost is given by,

$$R_{t=\tau} = \frac{\beta_{\text{reg}} + \beta_{\text{p}\times\text{reg}} p_{t=\tau}}{\beta_p + \beta_{\text{p}\times\text{reg}}} \quad (\text{A.3})$$

Table A.1 shows the results from estimating the specification in Equation A.1. Apart from the interaction term for partial units, the instruments show strong relevance for all price terms in the model. The model continues to exhibit a low degree of fit for partial units, with an adjusted R-squared of -0.7, whereas the fit is better for full units, with an adjusted R-squared of 0.68. Table A.2 shows that the standard deviation increases following enforcement, suggesting that the regulation has a heterogeneous impact across hosts, leading to increased dispersion in the cost distribution.

<b>Coefficient</b>	<b>Full Units</b>	<b>Partial Units</b>
$\beta_{0t}$ , const.	-3.022** (1.522)	-7.678* (4.522)
$\beta_{pt}$ , price	0.013* (0.008)	0.090* (0.055)
$\beta_{regt}$ , reg. ind.	-1.320 (1.964)	4.738 (7.278)
$\beta_{pxreg}$ , price x reg.	-0.001 (0.008)	-0.063 (0.059)
$\lambda_{0t}$ , time trend	-0.001* (0.000)	-0.004* (0.002)
$\lambda_{postt}$ , post-reg. trend	0.005*** (0.001)	0.009** (0.005)
Sample Size	1088	1088
F-statistic: Price	65.24	16.48
F-statistic: Price x Reg	21.27	7.26

Table A.1: Estimates for STRs using the flexible variance specification.

Notes: \*\*\* :  $p < 0.01$ , \*\* :  $p < 0.05$ , \* :  $p < 0.1$ . F-stat tests instrument relevance conditional on covariates. Fixed effects excluded from table. Sample size corresponds to number of days in the estimation period.

The mean costs over time, shown in Figure A.1, follow similar trends to those under the original specification, though the magnitudes are slightly attenuated. This is expected because the  $\beta_{pxreg} Reg_t$  term scales down the values in Equation A.2. Allowing the variance to change yields a more flexible specification that aligns more closely with prior expectations about the effects of regulation

Parameter	Full Units	Part Units
Mean pre-enforcement cost	234.34	99.41
Pre-enforcement std. dev.	75.93	11.06
Post-enforcement std. dev.	82.10	36.22
Mean shift at enforcement	129.16	119.32
Mean cost, Oct 2023	435.90	248.32

Table A.2: Cost parameters for STRs using the flexible variance specification.

on STRs. This in turn results in more reliable estimates. For MTRs, however, the modified model produces negative price coefficients, which in turn imply invalid (negative) values for standard deviations. Since Local Law 18 does not appear to affect MTRs (as shown in section 6.2), adding the additional interaction term likely results in a misspecified model for these markets. Accordingly, I do not report results for MTRs under this alternate specification.

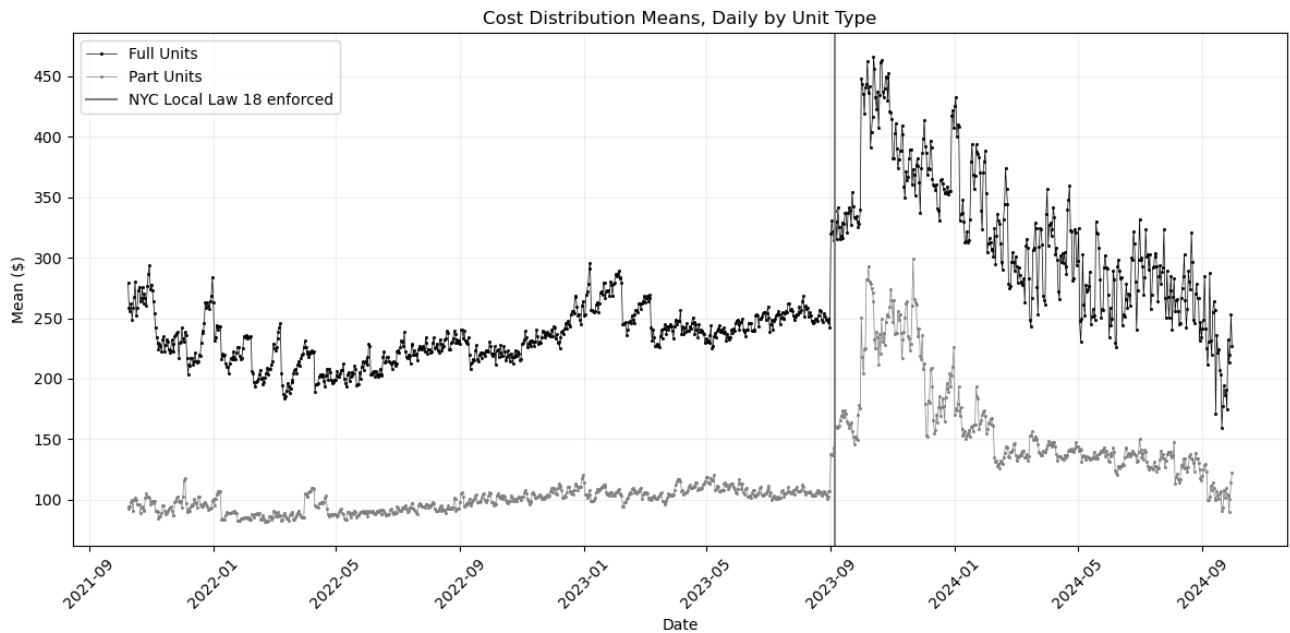


Figure A.1: Estimated peer-host cost distribution means through a specification that allows variance to change at enforcement.

APPENDIX B  
NON-EXITERS

Observed changes in hosting cost distributions reflect both shifts in the costs faced by incumbent hosts and changes in market composition, as hosts with differential costs enter or exit the market. In an attempt to isolate cost changes experienced by hosts that remain in the market after the regulation is enforced, I present results based on a restricted sample. I subset the data by excluding listings that are listed as STRs 10 days prior to enforcement, but are never seen in the STR market after October 1st, 2023. I choose this date to account for the lag arising from the periodicity of our data updates, and drop 1566 unique listings.

<b>Coefficient</b>	<b>Full Units</b>	<b>Partial Units</b>
$\beta_0$ , const.	-3.234* (1.823)	-10.106 (24.800)
$\beta_p$ , price	0.014 (0.009)	0.132 (0.340)
$\beta_{reg}$ , reg. ind.	-1.289** (0.632)	-6.562 (16.914)
$\lambda_0$ , time trend	-0.001*** (0.001)	-0.009 (0.023)
$\lambda_{post}$ , post-reg. trend	0.008*** (0.003)	0.032 (0.076)
Sample Size	1088	1088
First Stage F-statistic	7.51	0.17

Table B.1: Coefficient estimates for short-term rentals that do not exit at enforcement.

*Notes:* \*\*\* :  $p < 0.01$ , \*\* :  $p < 0.05$ , \* :  $p < 0.1$ . F-stat tests instrument relevance conditional on covariates. Fixed effects excluded from table. Sample size corresponds to number of days in the estimation period.

For this subset, price instruments are weak for both unit types (Table B.1). The price coefficients are positive but insignificant, and may be biased due to the lack of instrument relevance. Moreover, while the adjusted R-squared is 0.39 for full units, it is -23 for partial units. This poor fit likely stems from ex-

cluding the market exiters. If these were mostly hosts with higher costs from the right tail of the cost distribution, removing them would result in a truncated distribution that would violate the assumption under which hosts draw their marginal costs. Consequently, this method does not satisfactorily isolate cost changes for incumbent hosts, and refining the approach is left to future work on this project.

<b>Cost Parameter</b>	<b>Full Units</b>	<b>Part Units</b>
Mean cost, pre-enforcement	253.03	110.32
Cost std. dev.	70.80	7.59
Mean shift at enforcement	91.29	49.80
Mean cost, Oct 2023	399.17	216.92

Table B.2: Cost parameters for short-term rentals that do not exit at enforcement.

Though very likely biased, the recovered parameters in Table B.2 indicate that these hosts face lower cost increases. Compared to the results for all hosts in Table 6.2, hosts that remain in the STR market after Local Law 18 takes effect both experience smaller mean shifts on the day of enforcement and lower costs through October 2023. The trends in distribution means, presented in Figure B.1, closely mirror those observed for the full sample of hosts. Even within this subset, hosts offering prohibited full-unit STRs gradually exit the market, with higher-cost hosts leaving first.

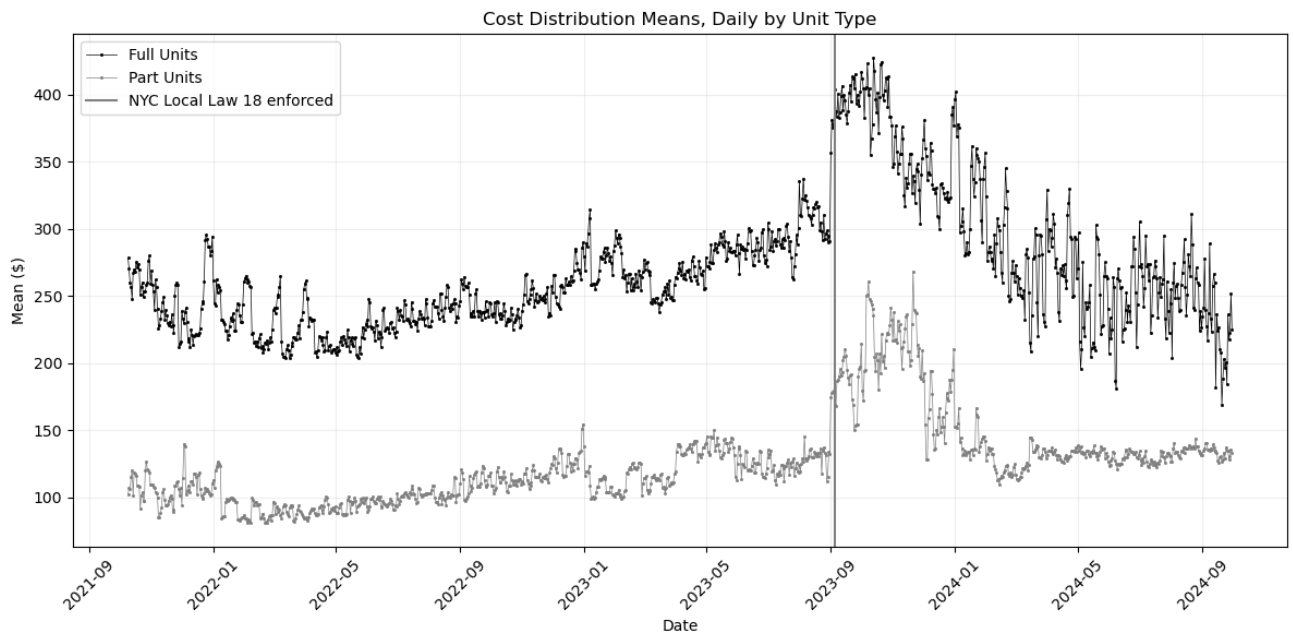


Figure B.1: Estimated peer-host cost distribution means for short-term rentals that do not exit the market at enforcement.

APPENDIX C  
INSTRUMENT VALIDITY

Since prices and quantities are simultaneously determined in equilibrium, estimating a supply curve by regressing a measure of quantity directly on price leads to biased estimates. To address this simultaneity problem, I use demand shifters as instruments for price. My instruments are five-year lagged, log-transformed, and de-trended Google search interest for the terms ‘*new york hotel*’ and ‘*things to do new york*’.

In terms of theory, the structural model I aim to estimate is given by,

$$Y_t = \beta_0 + \beta_p p_t + \lambda W + \varepsilon_t$$

Where  $Y_t$  represents the dependent variable and  $W$  is a vector with all other variables. Since supply shocks ( $\varepsilon_t$ ) affect both  $Y_t$  and  $p_t$  due to simultaneity,  $Cov(p_t, \varepsilon_t) \neq 0$ , and the  $\beta_p$  estimate from OLS is biased.

To arrive at an unbiased estimate I use demand shifters  $Z$ , which I assume are exogenous to supply, as instruments for price. The 2SLS estimator can be interpreted as estimating  $\beta_p$  in two stages,

$$p_t = \alpha + \pi Z + \rho W + \eta_t \quad (1st \text{ stage})$$

$$Y_t = \gamma + \beta_p \hat{p}_t + \lambda' W + \epsilon_t \quad (2nd \text{ stage})$$

The predicted prices from the first stage are used as the independent variable in the second stage. For  $Z$  to be valid instruments, two conditions must hold,

1. **Relevance:** The demand shifters are correlated with price, or  $\pi \neq 0$ .

2. **Exclusion restriction:** The demand shifters influence the outcome solely through their effect on price, or  $Cov(Z, \varepsilon_t) = 0$ .

For each estimation, I present the first-stage F-statistic as a test for relevance. This tests the null hypothesis that the instrument has no relevance for the price variable conditional on the covariates. The F-statistic is low for partial STR units, and particularly small for full MTRs. To diagnose this further for partial STRs, I present the bivariate relationships between instruments and prices in Figure C.1 and first stage estimates in Table C.1. One plot shows a negative relationship between prices and demand shocks, which is odd at first glance but signals that regulation and seasonality have a large influence on prices. After controlling for these, the first stage estimates mostly show strong positive correlations between demand and price, except for the hotel trend with partial units, where the estimate is insignificant. While this suggests excluding the hotel instrument for the supply estimation, doing so further lowers the F-statistic, and I therefore retain it.

	Full Units	Partial Units
Hotel Instrument	36.52*** (12.61)	-12.45 (9.25)
To-do Instrument	43.36*** (9.32)	17.44*** (6.03)

Table C.1: First-Stage OLS Estimates.

To further evaluate the correlation between the instruments and covariates, I use OLS to estimate the following model,

$$Z_t = \beta_0 + \beta_{reg} Reg_t + \lambda_0 \delta_t + \lambda_{post} \delta_{post} + \eta_{dw} + \gamma_{my} + \varepsilon_t$$

The adjusted R-squared values for this model are 0.49 and 0.54 for the hotel and to-do trends, respectively. While both instruments have a significant negative

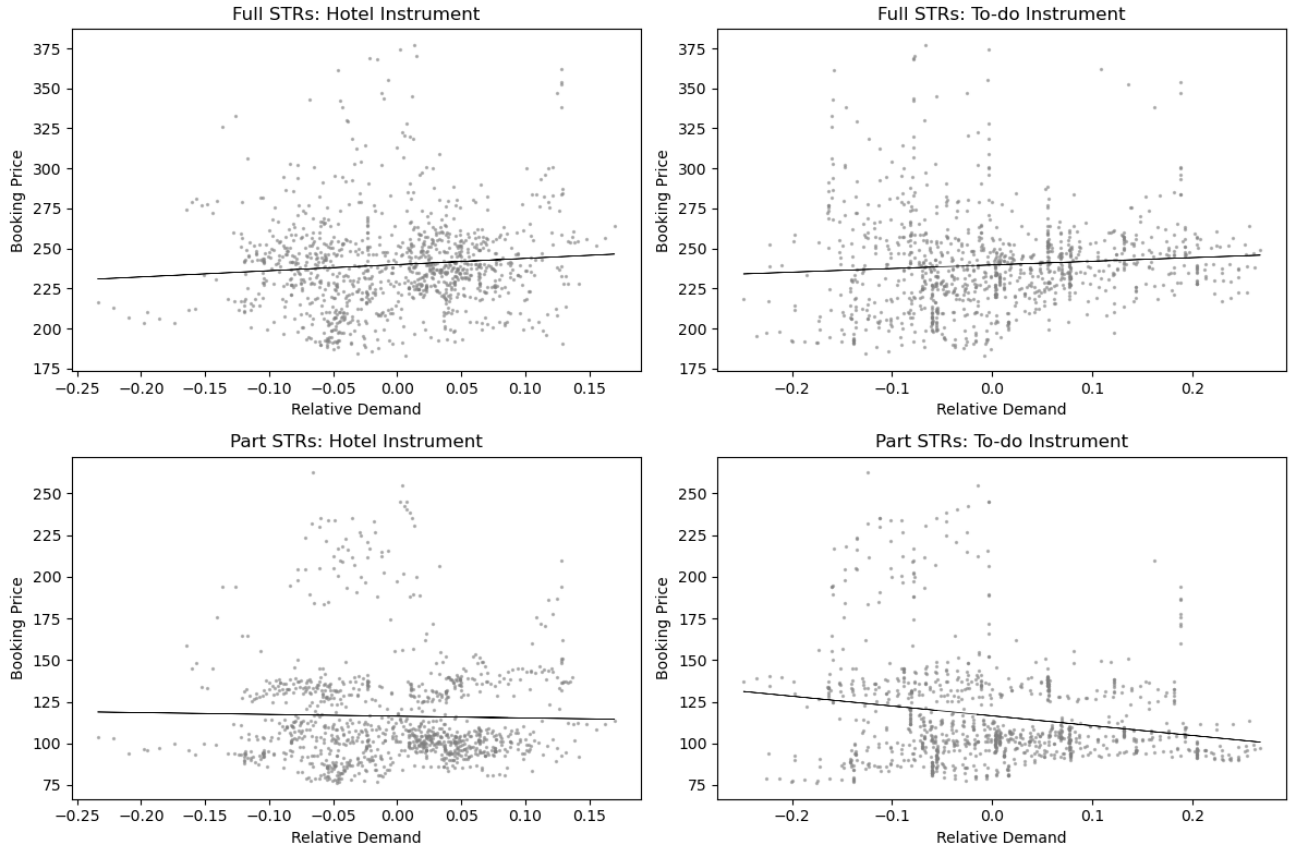


Figure C.1: First stage scatter-plots.

association with the regulation indicator, this is not causal since the trends are lagged by 5 years. Without  $Reg_t$ , the corresponding adjusted R-squared values are 0.45 and 0.51, indicating that the time fixed effects and linear trends themselves explain a considerable portion of the demand variation. Taken altogether, good demand-shifter instruments should theoretically show a strong positive correlation with price. In my work, this is not the case for partial units (Figure C.1). Moreover, the correlation between my instruments and the covariates used to estimate supply further reduces instrument strength.

The exclusion restriction cannot be tested directly, since  $\varepsilon_t$  from the true

structural model is unobserved. My instruments leverage within-year seasonal demand variation that systematically affects prices. This reflects the interest in visiting NYC throughout the year, and because I use search trends from five years prior, I argue that they are uncorrelated with contemporaneous supply shocks. Peer-hosts may (and probably do) respond to seasonality by increasing available listings, or through their seasonal hosting costs. I control for these using month and day-of-the-week fixed effects. Richer controls such as week fixed effects would reduce potential bias further, but they also impact instrument relevance, as discussed earlier.

As a rough diagnostic, I report the explained variance from the first-stage estimation to that of the reduced form, where I regress the dependent variable directly on the instruments. Ideally, the demand variation should explain more of the variation in prices than in equilibrium supply. The adjusted R-squared values from the first-stage and reduced-form regressions are 0.64 and 0.79 for full units, and 0.80 and 0.75 for partial units, respectively. Although the reduced-form value is higher for full units, this does not in itself indicate a breach of the exclusion restriction, since the higher explanatory power could arise mechanically and does not necessarily imply a direct causal effect of the instruments on supply.

[Farronato and Fradkin, 2022] use one-week lagged hotel searches as one of their instruments for price, stating that these are demand shifts from holidays or city events. They address possible reverse causality, or Airbnb availability influencing demand, by arguing this effect is unlikely given Airbnb's relatively small share of bookings compared to hotels. Since my instruments are lagged by 5 years, this is not an issue in my work. [Hidalgo et al., 2022] and

[Barron et al., 2020] use a shift-share instrumental variables approach to determine the treatment effect of Airbnb growth on their outcome variables, and use worldwide Google searches for Airbnb as their 'shift' instruments. They treat this as an exogenous driver of STR supply. The first paper examines Airbnb's impact on the restaurant industry in Madrid, while the second estimates effects on rents across the US. In both cases, search trends could plausibly influence outcomes directly by driving more tourism. To address this concern, the first paper argues that Airbnb's global scale makes any effect on local tourism negligible, while the second paper contends that worldwide search trends are unlikely to translate into measurable changes in local tourism within their short study window.

## BIBLIOGRAPHY

- [Almagro and Domínguez-Iino, 2025] Almagro, M. and Domínguez-Iino, T. (2025). Location sorting and endogenous amenities: Evidence from amsterdam. *Econometrica*, 93(3):1031–1071.
- [Barron et al., 2020] Barron, K., Kung, E., and Proserpio, D. (2020). The effect of home-sharing on house prices and rents: Evidence from airbnb. *Marketing Science*, 40(1):1–191.
- [Basuroy et al., 2020] Basuroy, S., Kim, Y., and Proserpio, D. (2020). Estimating the impact of airbnb on the local economy: Evidence from the restaurant industry. *SSRN Electronic Journal*.
- [Calder-Wang, 2021] Calder-Wang, S. (2021). The distributional impact of the sharing economy on the housing market. *SSRN Electronic Journal*.
- [Chen et al., 2022] Chen, W., Wei, Z., and Xie, K. (2022). The battle for homes: How does home sharing disrupt local residential markets? *Management Science*, 68(12):8589–8612.
- [Cui et al., 2020] Cui, R., Li, J., and Zhang, D. J. (2020). Reducing discrimination with reviews in the sharing economy: Evidence from field experiments on airbnb. *Management Science*, 66(3):1071–1094.
- [Dogru et al., 2020] Dogru, T., Hanks, L., Mody, M., Suess, C., and Sirakaya-Turk, E. (2020). The effects of airbnb on hotel performance: Evidence from cities beyond the united states. *Tourism Management*, 79:104090.
- [Fang et al., 2016] Fang, B., Ye, Q., and Law, R. (2016). Effect of sharing economy on tourism industry employment. *Annals of Tourism Research*, 57:264–267.
- [Farronato and Fradkin, 2022] Farronato, C. and Fradkin, A. (2022). The welfare effects of peer entry: The case of airbnb and the accommodation industry. *American Economic Review*, 112(6):1782–1817.
- [Franco and Santos, 2021] Franco, S. F. and Santos, C. D. (2021). The impact of airbnb on residential property values and rents: Evidence from portugal. *Regional Science and Urban Economics*, 88:103667.
- [Garcia-López et al., 2020] Garcia-López, M.-, Jofre-Monseny, J., Martínez-Mazza, R., and Segú, M. (2020). Do short-term rental platforms affect hous-

- ing markets? evidence from airbnb in barcelona. *Journal of Urban Economics*, 119:103278.
- [Gurran and Phibbs, 2017] Gurran, N. and Phibbs, P. (2017). When tourists move in: How should urban planners respond to airbnb? *Journal of the American Planning Association*, 83(1):80–92.
- [Guttentag, 2015] Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, 18(12):1192–1217.
- [Han et al., 2021] Han, W., Wang, X., Ahsen, M. E., and Wattal, S. (2021). The societal impact of sharing economy platform self-regulations—an empirical investigation. *Information Systems Research*, 33(4):1303–1323.
- [Hidalgo et al., 2022] Hidalgo, A., Riccaboni, M., and Velázquez, F. J. (2022). The effect of short-term rentals on local consumption amenities: Evidence from madrid. *SSRN Electronic Journal*. Last revised February 1, 2024.
- [Horn and Merante, 2017] Horn, K. and Merante, M. (2017). Is home sharing driving up rents? evidence from airbnb in boston. *Journal of Housing Economics*, 38:14–24.
- [Jefferson-Jones, 2015] Jefferson-Jones, J. (2015). Airbnb and the housing segment of the modern sharing economy: Are short-term rental restrictions an unconstitutional taking? *Hastings Constitutional Law Quarterly*, 42(3):557–580.
- [Jia and Wagman, 2020] Jia, J. and Wagman, L. (2020). Platform, anonymity, and illegal actors: Evidence of whac-a-mole enforcement from airbnb. *Journal of Law and Economics*, 63(4):729–761.
- [Jin et al., 2024] Jin, G. Z., Wagman, L., and Zhong, M. (2024). Short-term rental regulation: Insights from chicago. *International Journal of Industrial Organization*, 96:103087. The 50th Annual Conference of European Association for Research in Industrial Economics, Rome, 2023.
- [Kim et al., 2025] Kim, M., Darban, M., and Lim, S. E. (2025). The impact of airbnb’s competitive pricing on traveler spending at destinations. *International Journal of Hospitality Management*, 124:103994.
- [Koster et al., 2021] Koster, H. R., van Ommeren, J., and Volkhausen, N. (2021).

- Term rentals and the housing market: Quasi-experimental evidence from airbnb in los angeles. *Journal of Urban Economics*, 124:103356.
- [Kytömaa, 2019] Kytömaa, L. (2019). Regulation, market structure, and housing affordability: An investigation of airbnb's decline in san francisco. Available at SSRN: <https://ssrn.com/abstract=4517828>.
- [Li and Srinivasan, 2019] Li, H. and Srinivasan, K. (2019). Competitive dynamics in the sharing economy: An analysis in the context of airbnb and hotels. *Marketing Science*, 38(3):365–391.
- [Lin et al., 2022] Lin, J., Nian, T., and Gurbaxani, V. (2022). Impacts of the sharing economy entry and regulations on financial delinquencies. *SSRN Electronic Journal*.
- [Maldonado-Guzmán, 2022] Maldonado-Guzmán, D. J. (2022). Airbnb and crime in barcelona (spain): Testing the relationship using a geographically weighted regression. *Annals of GIS*, 28(2):147–160.
- [Nieuwland and van Melik, 2020] Nieuwland, S. and van Melik, R. (2020). Regulating airbnb: How cities deal with perceived negative externalities of short-term rentals. *Current Issues in Tourism*, 23(7):811–825.
- [Schaefer and Tran, 2020] Schaefer, M. and Tran, K. D. (2020). Airbnb, hotels, and localized competition. *DIW Berlin Discussion Paper No. 1889*. Available at SSRN: <https://ssrn.com/abstract=3676907>.
- [Schneiderman, 2014] Schneiderman, E. T. (2014). Airbnb in the city. Technical report, Office of the Attorney General, State of New York. Prepared by the Research Department and Internet Bureau.
- [Stock and Yogo, 2005] Stock, J. H. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. In Andrews, D. W. K. and Stock, J. H., editors, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, pages 80–108. Cambridge University Press. Available at SSRN: <https://ssrn.com/abstract=1734933>.
- [Valentin, 2021] Valentin, M. (2021). Regulating short-term rental housing: Evidence from new orleans. *Real Estate Economics*, 49(1):152–186.
- [Voltes-Dorta, 2024] Voltes-Dorta, A. (2024). Price competition among short-

term airbnb listings in new york city following local law 18. *Current Issues in Tourism*, pages 1–5.

[von Briel and Dolnicar, 2021] von Briel, D. and Dolnicar, S. (2021). The evolution of airbnb regulations. In Dolnicar, S., editor, *Airbnb Before, During and After COVID-19*. University of Queensland.

[Wachsmuth and Weisler, 2018] Wachsmuth, D. and Weisler, A. (2018). Airbnb and the rent gap: Gentrification through the sharing economy. *Environment and Planning A: Economy and Space*, 50(6):1147–1170.

[Williams, 2020] Williams, K. R. (2020). Dynamic airline pricing and seat availability. *Cowles Foundation Discussion Paper*, (2103R). Available at SSRN: <https://ssrn.com/abstract=3611696>.

[Xu and Xu, 2021] Xu, M. and Xu, Y. (2021). What happens when airbnb comes to the neighborhood: The impact of home-sharing on neighborhood investment. *Regional Science and Urban Economics*, 88:103670.

[Zervas et al., 2017] Zervas, G., Proserpio, D., and Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of airbnb on the hotel industry. *Journal of Marketing Research*, 54(5):687–705.