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**Dynamic vs. Fixed Pricing in Urban Mobility:
An Empirical Analysis of Fare Sensitivity in Taxi Services**

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Abstract

This thesis examines the interplay across diverse mobility options in New York City, focusing on cost variability and commuter behavior. This work investigates the evolution of fare disparities between taxis, using comprehensive datasets from NYC's Taxi and Limousine Commission. The study revealed how commuter choices are influenced by operational regions and pricing models: key findings highlight significant temporal and spatial fare trends. A comparative analysis of dynamic versus fixed pricing models showcased the flexibility of ride-hailing platforms like Uber in addressing peak demands and spatial variations, differing from the rigidity observed in traditional pricing systems. These analyses provide critical insights into spatiotemporal variations in taxi demand, including the differential impacts of demographic factors. The findings aim to guide policymakers in developing adaptive and sustainable mobility strategies tailored to the evolving urban landscape.

Keywords

Urban mobility, Geo-specific Analysis, Trend Analysis, Ride-hailing Services, Fare Elasticity

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1. Introduction

Urban mobility systems are critical to the functioning of modern cities, enabling the movement of millions of individuals daily while shaping economic, social, and environmental outcomes. In New York City (NYC), a city renowned for its dense population and complex infrastructure, transportation services play a pivotal role in supporting urban life. Over the years, NYC's transportation landscape has evolved significantly, reflecting changes in commuter needs, technological advancements, and policy-driven reforms. Central to this system are its taxi services, which range from traditional yellow and green taxis to app-based ride-hailing platforms like Uber and Lyft, and the broader network of public transit systems such as buses and subways.

Despite this diversity, challenges such as geographic inequities, congestion, and fluctuating demand persist, necessitating a deeper understanding of how different mobility modes interact and adapt within the city's unique urban environment. Efforts to expand and diversify NYC's transportation network have resulted in significant changes to its taxi ecosystem. Historically dominated by yellow taxis, the introduction of green taxis sought to extend services to underserved areas like Brooklyn, Queens, and the Bronx. These changes raised questions about how increased taxi coverage has influenced commuter behavior in the outer boroughs. Has this initiative successfully addressed gaps in accessibility, or has it merely shifted existing dynamics? Understanding these spatial patterns offers insights into the effectiveness of such policy-driven expansions.

At the same time, the interplay between public transit systems and taxi services highlights the interconnectedness of NYC's mobility ecosystem. Public buses, often serving as a lifeline for disadvantaged communities, experience competition and complementarities with taxis, especially in areas where subway access is limited. Changes in bus service availability, delays, or coverage can influence taxi usage, creating ripple effects across the transportation network.

Exploring these dynamics sheds light on how public and private modes of transport coexist and compete within a constrained urban space.

Pricing models further complicate NYC's mobility landscape. The cost differences between yellow and green taxis provide a lens to examine how operational areas and fare structures influence commuter choices. These variations reflect not only economic factors but also temporal and spatial nuances, revealing how fares align—or fail to align—with demand patterns. While green taxis aim to serve peripheral neighborhoods, the cost dynamics between the two services prompt questions about fairness, efficiency, and accessibility. The emergence of app-based ride-hailing services such as Uber and Lyft has introduced new layers of complexity to NYC's transportation system. These platforms, offering flexibility and convenience, cater to a wide range of travel purposes, from routine commutes to leisure activities. By comparing trip patterns between green taxis and ride-hailing services, it is possible to uncover how user preferences and behaviors diverge across different modes. These insights are critical for understanding the broader implications of these services on traditional taxi operations and commuter mobility.

Underlying many of these discussions is the tension between fixed and dynamic pricing models. Traditional taxis operate under regulated pricing systems, offering predictability but limited adaptability to changing conditions. In contrast, ride-hailing platforms leverage dynamic pricing algorithms to adjust fares in real time based on demand and traffic. These distinct approaches offer a unique opportunity to explore how pricing strategies influence fare sensitivity and commuter decision-making, especially in a city as multifaceted as NYC. This is why this thesis investigates several interconnected research angles of New York City's transportation systems: by examining the evolution of fare disparities between yellow and green taxis, along with employing advanced predictive models to understand cost variations over time and space, it was possible to show high variability in cost differences between comparable taxi

rides and the consequent difficulty in predicting those values. Additionally, green taxis primarily serve outer boroughs with stable fares, while yellow taxis dominate central Manhattan, often with higher and more variable costs during peak hours and weekends, highlighting how operational zones and service shape commuter behavior. Moreover, this study reveals how shifts in taxi coverage influence subway ridership in underserved areas of NYC. Another aspect involves evaluating the impact of dynamic pricing models as seen in ride-hailing platforms like Uber and contrasting them with traditional systems used by taxis. This led to a deep understanding of flexibility and efficiency in addressing peak demand and spatial variability.

2. Literature Review

2.1 Foundations of Urban Mobility

Urban mobility describes the systems, services, and infrastructure that enable the movement of people and goods within urban areas. It is defined as the integration of multiple transportation modes, such as public transit, private vehicles, shared mobility, walking, and cycling, and it aims to address challenges of accessibility, sustainability, and equity. Its scope comprises multimodal systems for seamless travel, sustainability efforts to reduce environmental impact, and the adoption of advanced technologies like AI and ICT to improve efficiency and user experiences. An important aspect of urban mobility is to ensure economic and social equity, making transportation affordable and accessible for all residents while balancing environmental and economic goals (Arthur D. Little, 2011). The evolution of urban transportation systems was influenced by sociopolitical and historical developments. In pre-20th-century cities, compact and walkable designs dominated, with limited mechanized transport. The post-war era saw a surge in car ownership, resulting in investments in road networks and the neglect of tram systems in many urban areas. However, some cities, such as Karlsruhe, maintained and innovated tram networks, in contrast to car-centric developments in other cities. The late 20th century saw a rebirth of interest in sustainable transit, which led to innovations like tram-train systems and integrated urban planning (Pflieger, 2009). To this day, private cars remain dominant globally, accounting for 45% of trips. However, projections suggest a 15% decline by 2035, driven by the growth of autonomous vehicles and micromobility (McKinsey & Company, 2023). Urban transportation systems show path dependencies, where historical decisions, such as the introduction or removal of tram systems or the growth of private car ownership, create lasting influences on urban policies and infrastructure. The high cost of reversal locks cities into specific development trajectories unless significant crises or innovations occur (Pflieger, 2009). New York City shows unique urban mobility characteristics

shaped by its geography and central transportation hubs. Sustainable transportation modes, such as walking, biking, and public transit, account for more than two-thirds of all trips. NYC's dense urban cores, particularly in Manhattan and key business districts, play a critical role in that. The Central Business District (CBD) experiences heavy congestion, with sustainable transportation accounting for 78% of trips into the area. Public transit remains vital for most residents, although aging infrastructure and telecommuting have caused slight declines in subway use (New York City Department of Transportation, 2019). Programs like Citi Bike illustrate the emergence of micromobility, reshaping short-distance travel in areas like Midtown Manhattan (Sun & Axhausen, 2016).

NYC's mobility patterns reflect interconnected yet constrained boroughs, with bridges and tunnels serving as critical, often congested nodes. The growth of freight and e-commerce is adding pressure to urban traffic systems. Geographical constraints, such as the city's island structure, limit road expansion and shift the focus to efficient public and shared transportation. Additionally, high tourist volumes, especially in areas like Times Square, require special mobility solutions for localized travel (New York City Department of Transportation, 2019).

2.2 Role of Taxis in NYC's Urban Mobility

Taxis have been a significant part of New York City's transportation landscape for decades. They serve as a key alternative to public transit, particularly in areas with limited-service coverage, and for seniors and individuals with mobility challenges (New York City Department of City Planning, 2009). Historically, NYC's taxi system was governed by the medallion system, which regulated the number of cabs operating within the city. However, the rise of app-based ride-hailing services, such as Uber and Lyft, has caused a significant decline in traditional yellow taxi usage, reshaping urban mobility patterns and changing urban transportation planning. The transition from medallion taxis to ride-hailing services indicates a broader shift

in consumer preferences, technological adoption, and the evolving role of taxis in the city's transportation structure (Moro, 2021; New York City Department of City Planning, 2009). This changing landscape has significant implications for urban planning and mobility strategy in NYC. As ride-hailing services increasingly dominate, the city must address issues of equity, congestion, and sustainability to ensure that taxis, both traditional and app-based, continue to contribute effectively to the broader transportation network (Moro, 2021).

2.3 Socio-Economic and Demographic Factors Influencing Urban Mobility in NYC

Income inequality significantly impacts access to transportation options in New York City, showing mobility inequalities among different socio-economic groups. Lower-income individuals face barriers, such as high taxi costs and inconsistent public transport availability in underserved neighborhoods, limiting their ability to access essential services like jobs and healthcare (New York City Department of City Planning, 2009). In contrast, wealthier residents benefit from better access to diverse transportation modes, including taxis and ride-hailing services, and are more likely to explore geographically diverse areas, reducing experienced segregation (Moro, 2021). High-income areas, particularly in central Manhattan, are dominated by yellow taxis, while peripheral and low-income areas often rely on less reliable livery cabs or limited public transit options, deepening mobility inequalities (New York City Department of City Planning, 2009). This dynamic reinforces systemic segregation and unequal access to opportunities, as residents in these areas face constraints tied to economic and infrastructural limitations (Moro, 2021). Work-from-home (WFH) and hybrid work models have also transformed commuting patterns in the city. While these models have reduced rush-hour congestion, they have increased off-peak traffic, particularly in areas with flexible work environments. This shift required adaptations in transit schedules and infrastructure to adapt to the changing traffic flows (Lasley, 2021).

2.4 Public Policy and Governance in Urban Mobility

By aiming to address social equity, environmental sustainability, and technological advancements, public policy and governance play a critical role in shaping urban mobility systems. While stable political regimes rather reinforce existing policies, institutional and political changes either strengthen innovation or serve as barriers to reform. Urban transport policies, such as integrated planning in cities like Grenoble, demonstrate how aligning transportation with urban development can result in significant social and spatial benefits, including reduced car reliance and improved accessibility (Pflieger, 2009). Urban and transport planning also have direct health implications. Proper planning can mitigate key urban exposures, such as air pollution, noise, and urban heat islands, while enhancing access to green spaces and opportunities for physical activity (Nieuwenhuijsen, 2016). Community-level interventions, such as promoting green spaces and reducing car reliance, have proven more cost-effective and impactful than individual-level efforts. These strategies emphasize equitable access to transport systems, bridging the gap between income-segregated communities by expanding affordable public transit and reducing cost barriers for taxis (Moro, 2021). In New York City, regulation is a key tool for managing mobility challenges. The medallion system historically controlled the taxi industry, while congestion pricing programs are now being introduced to reduce vehicle volumes in the Central Business District (Miskolczi, 2021; New York City Department of Transportation, 2019). Cities worldwide are adopting similar measures, including parking restrictions, car-free zones, and dynamic tolling, to manage traffic and pollution. Such strategies are crucial in balancing technological advancements with societal acceptance and legal frameworks, especially for innovations like autonomous vehicles (Bouton, 2015).

Public-private partnerships (PPPs) further address urban mobility challenges by fostering

collaboration between governments, private companies, and tech innovators. These partnerships accelerate the deployment of solutions like electric vehicle (EV) charging stations, shared mobility platforms, and autonomous vehicle (AV) pilot projects. For example, governments can subsidize shared mobility services, provide tax benefits for EV adoption, and promote subscription-based services to encourage behavioral shifts toward sustainable mobility (Miskolczi,2021;Butler,2020;Kamargianni,2016).

Finally, governance frameworks must address data privacy and transparency, ensuring user trust while leveraging mobility data for planning and optimization. Policies supporting AV integration, such as liability guidelines and safety standards, can build public confidence and accelerate adoption (Miskolczi, 2021). By investing in intelligent transportation systems (ITS), high-speed internet, and secure communication networks, cities can establish the foundations for smart infrastructure and future-ready urban mobility systems (Butler, 2020).

2.5 Technological Innovations and Smart Mobility in NYC

Technological innovation in urban mobility is expected to play an important role in dealing with the growing transportation challenges. Over-reliance on private vehicles and outdated infrastructure is pushing many urban mobility systems toward breakdown. To address these challenges, advancements in automation, shared mobility, and electrification are transforming urban transportation systems (Miskolczi, 2021). Services like Uber and Lyft have revolutionized urban transit by introducing e-hailing, car sharing, and on-demand shuttles. These innovations are driving a decline in car ownership, especially among younger generations in developed nations, as preferences shift toward shared mobility. Mobility-as-a-Service (MaaS) platforms exemplify this transformation by integrating public transit, car sharing, and bike-sharing into a single, seamless system (Bouton, 2015). Through real-time data sharing and journey planning, MaaS offers door-to-door mobility while reducing reliance on personal

vehicles (Butler, 2020). However, its implementation faces challenges, such as limited integration across operators, complex revenue-sharing models, and varied user willingness to pay for subscription-based services (Kamargianni, 2016). Shared mobility services, including dockless bike-sharing programs and app-based ridesourcing, address critical issues like first- and last-mile connectivity. They also deliver environmental benefits by reducing vehicle miles traveled and decreasing road congestion. These innovations are key to strengthen multimodal travel, sustainability, and urban accessibility (Butler, 2020). Emerging technologies like big data and the Internet of Things (IoT) are central to modern urban traffic management. Inefficiencies in urban mobility currently cost cities 2–4% of their GDP due to wasted time and resources (Bouton, 2015). Intelligent Transportation Systems (ITS) integrate advanced ICT and real-time analytics to optimize transportation networks. Applications include adaptive traffic signal control, incident detection, and dynamic scheduling for public transit. Additionally, networked ecosystems, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems, promise enhanced safety and traffic flow (Lasley, 2023; Moss, 2012; Butler, 2020). The transition to electric and autonomous vehicles (AVs) is redefining urban mobility. Electric vehicles (EVs) significantly improve energy efficiency and reduce emissions (Moss, 2012; Bouton, 2015). Meanwhile, AVs, capable of navigating without human input, hold the potential to reduce road accidents by up to 90%, increase traffic efficiency, and provide mobility options for individuals without driving licenses. However, challenges, such as cybersecurity risks, ethical dilemmas during accidents, and infrastructure readiness, remain significant barriers to widespread adoption (Butler, 2020). Adoption might remain slow due to economic and social barriers, which highlights the need for regulatory clarity and collaborative efforts across sectors (Bouton, 2015). Crucial for supporting these innovations are investments in smart infrastructure, including electric vehicle charging networks and data processing for traffic management (Moss, 2012).

2.6 Comparative Studies and Lessons from Other Cities

New York City may benefit from examining sustainable and innovative mobility practices implemented in other global cities. One significant area of innovation is the development of Mobility-as-a-Service (MaaS) platforms. Cities like Helsinki and Gothenburg have pioneered MaaS initiatives, such as UbiGo, which integrate various transit modes into a single, seamless system. These platforms allow users to plan, book, and pay for multi-modal journeys across different transport providers, simplifying access to sustainable transport and reducing reliance on personal vehicles (Bouton, 2015; Kamargianni, 2016). Other examples of successful MaaS implementations include the Octopus card in Hong Kong and the Oyster card in London. These smart card systems have significantly increased public transit usage by offering a unified payment method for various modes of transportation, including buses, subways, and ferries. The convenience and efficiency provided by these integrated systems highlight the potential for MaaS to transform urban mobility by promoting multimodal travel and making public transportation more user-friendly (Butler, 2020). However, transferring global best practices to New York City's context requires careful consideration of the city's unique characteristics. Different city types—such as megacities, rising cities, and car-dominated cities—experience unique mobility evolutions based on factors like density, existing infrastructure, and available resources. For instance, while NYC shares similarities with other megacities in terms of scale and complexity, its legacy infrastructure and regulatory environment may present challenges not encountered in cities like Helsinki or London (Bouton, 2015).

2.7 Emerging Trends and Future Challenges in Urban Mobility

Urban mobility is experiencing significant transformations driven by emerging trends and future challenges. By 2030, 60% of the global population will live in cities, intensifying

pressure on urban infrastructure (Moss, 2012; Bouton, 2015). Integrating urban mobility with land-use planning is becoming essential for future development, ensuring that transportation systems align with urban growth strategies and environmental objectives (Bouton, 2015). There is a growing reliance on mixed transportation modes, including public transit, car-sharing, biking, and walking. This shift indicates urban residents' increasing preference for connectivity and access over private car ownership (Moss, 2012). Reallocating urban space is another emerging trend aimed at enhancing the quality of urban life. This involves repurposing areas previously dedicated to parking for green spaces, bike-sharing docks, or electric vehicle (EV) charging stations. Introducing car-free zones and low-emission areas helps reduce congestion and pollution, improving urban quality of life (Moss, 2012; Moskolczi, 2021). The traffic composition is also evolving. Congestion has increased due to the surge in e-commerce demand, leading to significant delays during peak periods, especially in densely populated urban areas (Lasley,2023).

Key challenges include the slow adoption of innovations due to economic and social barriers, the need for integrated infrastructure to support shared and autonomous systems, and balancing technological advancements with societal acceptance and legal frameworks (Miskolczi, 2021). These emerging trends and challenges highlight the necessity for cities like New York to adapt and innovate. Embracing integrated planning, promoting multimodal transportation options, and preparing for future demographic shifts are crucial steps toward creating a resilient and efficient urban mobility system.

3. NYC Transportation Industry Overview

3.1 The historical development of NYC's transportation system

The transportation system of New York City lays the foundation of the world's most dynamic city, reflecting centuries of technological development, policy experimentation, and adaptation. The system comprises ferries, buses, subways, and taxis and regularly makes more than 8.5 million trips each day to meet the needs of New York City's growing population, tourism, and economy. We're going to trace the development of NYC's transportation system especially buses, subways, and taxis, providing the historical context needed to understand the interconnections and evolution of urban mobility in New York City.

Buses: From Horsepower to High-Tech

Beginning with horse-drawn omnibuses, NYC's bus system developed in the early 19th century. These basic buses traveled along fixed routes and charged fares of 12.5 cents, or \$4.50 today. By the 1850s, omnibuses were being replaced by horse-drawn streetcars, allowing for more speed and capacity. Electric trolleys appeared in the 1880s, allowing a new era of mechanized transit.

Motorized buses hit New York City streets in 1907 with the Fifth Avenue Coach Company, offering a cleaner, more efficient alternative to horse-drawn systems. The city purchased private bus lines during the Great Depression and brought all operations under public control by the 1940s. By 1950, buses were carrying 2.3 million daily passengers, connecting neighborhoods often not served by the subway. Select Bus Service (SBS), introduced in 2008, modernized the bus network and reduced travel times by 20–30% with features such as off-board fare collection and dedicated lanes. By 2020, NY's buses served 1.2 million daily riders, down from their mid-20th-century peak but still important for underprivileged areas. Recent efforts have turned to

electrification; in 2022, the MTA announced that it planned to switch its entire fleet to zero-emission buses by 2040.

Subways: The Backbone of Urban Transit

The subway system, one of the most important components for public transportation, originates back to the overcrowded streets of the 19th century, where the trains or “El trains” provided the first solution. The first subway line, run by the Interborough Rapid Transit Company (IRT), opened on Oct. 27, 1904. Its first day of service had more than 150,000 passengers, running from City Hall to 145th Street. The fare was fixed at five cents, an affordable method of transportation for the city’s working class. In the early years, the IRT and other systems that emerged together to become known as the Brooklyn-Manhattan Transit (BMT) system funded a massive expansion dubbed the Dual Contracts, doubling the size of the network by 1913. In 1940, the IRT, BMT, and the Independent Subway System (IND) were unified under public control, simplifying fares and operations, which resulted in 2 billion trips annually by the 1950s. The ’70s and ’80s were dark decades for the subway. Underfunding, poor maintenance, and rising crime impacted ridership to record the lowest rates, which made the M.T.A. launch a \$54 billion capital program to improve infrastructure by 1981, including replacing the old tracks and rolling stock. In 1993, the MetroCard was launched, a switch to modernization for both subway and bus systems, and in 2000, more major investments were made to gain public trust, which led us to today. Comprising 472 stations, the subway serves about 5 million weekday riders, about 68% of New Yorkers. Its ongoing rollout of OMNY contactless payments and accessibility upgrades is proof of its commitment to modernizing its network. However, challenges still exist, including old infrastructure, delays, and declining ridership in a post-COVID world that still needs improvements and consistent investments.

Taxis: From Hackney Carriages to Uber Dominance

New York City's taxi industry has been an essential component of the city's transportation system since the mid-19th century, when horse-drawn hackney carriages first traveled the cobblestone streets. These early carriages were used as a luxurious service on demand for wealthier residents by charging passengers for rides between locations. The New York Taxicab Company appointed gasoline taxis in 1907, with 600 painted bright red and green. Motorized cabs gained popularity because they were a faster and more reliable option in comparison with horse-drawn alternatives. By 1910, over 1,000 gasoline-powered cabs flooded the streets of NYC, paving the way for the modernized industry seen today. In the 1920s, Hertz Rent-A-Car founder John Hertz debuted the iconic yellow taxi that we know today. The yellow color was selected because a 1960s study concluded it was the most visible color from a far distance, allowing passengers to identify taxis easily in the thriving streets of Manhattan. By the 1930s, taxis were a familiar sight on New York City's streets, providing cheap, convenient rides for a growing population. The medallion system was introduced in 1937 to regulate how many cabs could operate in the streets and to guarantee a certain level of service. The system limited the number of medallions to 13,595, a figure that remained constant for decades. Although this policy increased accountability and system stability, it blocked potential players, new drivers, and organizations from entering the industry. By the mid-20th century, medallion ownership had become a significant investment with values surpassing \$1 million. By the early 2010s, Uber and other ride-hailing services were upending the taxi industry, shaking its dominance and reshaping the transportation market. Uber's app-based platform debuted in 2011 with upfront prices, shorter wait times, and convenient fares. Within a year, ride-hailing services began to appear, with Lyft also taking a significant market share. In 2018, NYC advanced a cap on growth, aiming to decrease the number of ride-hailing vehicles on the streets to stop oversaturation. The city launched congestion pricing zones in Manhattan to ease traffic flow

and balance the competition between taxis and ride-hailing services. But the medallion system, which had always been stable and served as a symbol of the taxi industry, crashed. Medallion values hit rock bottom, leaving many owners bankrupt and their investments worthless. By 2019, the effect of ride-hailing was indisputable. In NYC alone, Uber recorded 91 million trips, while yellow cabs took just 77 million trips. In recent years, the focus has shifted to sustainability and accessibility. New York City, in 2022, started a pilot program to replace older taxis with electric models, aiming to electrify a third of the taxis by 2030. Still, challenges remain since the current system doesn't prioritize the needs of wheelchair-accessible vehicles (WAVs) and disabled passengers. While yellow cabs are an iconic symbol of New York City, their continued relevance in the face of changing consumer preferences and technology is a question mark. Ensuring that taxis are not just a prominent mode in the city's multimodal transportation future will require further digitized platforms, sustainable vehicles, and regulations focused on equity.

From subways breaking down barriers of surface congestion and enabling mass transit easily across the city, buses improving access to underserved neighborhoods, and taxis providing on-demand service, each mode of transportation has had a unique impact on the city's growth, boosting tourism and supporting the economy. They together represent not only technological progression but also NYC's capacity to adjust to the needs of an ever-evolving city. This evolution allows us to see in what measure different transportation modes influence each other.

3.2 Key Boroughs of New York City: Economic and Cultural Centers

The city's transportation system is thus a lifeline for its residents. There are several high-density populated areas located in New York, which serve as the focal point for a lot of the economic and cultural activities of the city. Areas such as Downtown Brooklyn, Flushing Queens, Midtown Manhattan, and Bronx Grand Concourse are some of

these key areas, which cluster a lot of the city's economic and cultural activities. Let us investigate some of the key characteristics of the 5 boroughs of New York City.

Manhattan: It is the financial and cultural heart of the city. During the day, it has the highest population density in the world because of its accumulation of businesses and cultural attractions. Iconic neighborhoods like Midtown Manhattan and the Financial District are served by key transportation hubs such as Grand Terminal Station and the Port Authority Bus Terminal.

Brooklyn: Once a center for docks and factories, it has rapidly gentrified at the turn of this century into one of New York's most iconic and influential areas. Between 2010 and 2015, it has seen the greatest number of jobs being added compared to any of the boroughs outside Manhattan, adding 106,000 jobs. Its location serves to be a key area for the city's transportation network, as it connects the residential areas of Long Island with Manhattan via bridges, tunnels, and the subway.

Queens: It is the most ethnically diverse borough of the city, having some of the highest numbers of foreign-born residents, accounting for 47% of its population. It serves as a major residential zone in the city, having key population clusters such as Flushing and Jamaica. It also hosts the two main airports of New York: La Guardia and JFK Airport.

Bronx: It is a traditionally underserved region of New York, largely being a residential hub for the relatively poor population of the city. It is located very close to Manhattan, thereby making it a key source of labor for the city's economy. It also faces some of the highest commuting times of any of the boroughs in the city. The Metro-North commuter rail serves as the major transportation lifeline for its residents.

Staten Island: It is the least densely populated area of the city, characterized by its suburban setting and relative disconnection from the rest of the city. Often referred to as the 'forgotten borough' of the city, it has the highest rates of car ownership in the city, which is highlighted

by the limited public transportation options available. The Staten Island Ferry serves as a major link to its residents, connecting them to Manhattan, whereas the Verrazano-Narrows Bridge provides the crucial roadway linkage to Brooklyn.

3.3 Pricing models and Regulations

Yellow Taxis and the Medallion System

To ensure accuracy, historically, taxi fares were calculated using mechanical or electronic taximeters calibrated periodically, with prices based on time and distance. Consequently, operational costs—fuel prices, maintenance, and inflation—led to occasional fare adjustments. This is why fixed meter rates were often revised annually or in response to economic changes. This system was created to control the number of taxis on city streets, ensuring service quality, driver income stability, and market predictability. The medallion became a tradable commodity, its value fluctuating with market demand and TLC policies. Yellow taxis primarily operate in Manhattan and nearby areas, where street-hail demand is highest. They are equipped with meters that calculate fares based on time and distance, with additional surcharges for specific conditions:

- **Peak Hours:** An extra fee applies during weekday rush hours.
- **Congestion Surcharge:** A flat fee of \$2.50 is levied for trips below 96th Street in Manhattan, introduced in 2019 to alleviate traffic and support public transit funding.

Despite their dominance, yellow taxis have faced criticism for limited coverage outside central Manhattan and for their rigidity in responding to real-time fluctuations in demand.

Introduction of Green Taxis (Boro Taxis)

In response to the geographic service disparity, TLC introduced green taxis, also known as Street Hail Liveries (SHLs), in 2013. These vehicles were designed to address the transportation needs of NYC's underserved outer boroughs (Brooklyn, Queens, Staten Island, and the Bronx)

and northern Manhattan. Unlike yellow taxis, green taxis are prohibited from picking up street hails in Manhattan's central business district and at city airports, except through pre-arranged rides.

Green taxis operate under the same regulated pricing model as yellow taxis, with fares determined by meters based on time and distance. The introduction of green taxis marked an important step in addressing the transportation inequities in NYC, providing more accessible and affordable options for residents in low-demand areas.

Operational and Regulatory Distinctions

The distinction between yellow and green taxis extends beyond geography to operational and market dynamics:

- **Street Hail Zones:** Yellow taxis have exclusive rights to street hails in central Manhattan, while green taxis serve outer boroughs.
- **Meter-Based Pricing:** Both services share the same regulated pricing structure, but green taxis rarely encounter high-density zones with congestion surcharges.
- **Licensing and Oversight:** Both are regulated by the TLC, ensuring driver and passenger safety, service quality, and fare transparency.

While both services follow traditional meter-based pricing, the geographic segmentation reflects an attempt to balance demand across the city, mitigating the dominance of yellow taxis in high-traffic areas while extending service to underserved regions.

The Emergence of For-Hire Vehicles (FHVs) and Ride-Hailing Platforms

The for-hire vehicle (FHV) sector has long complemented NYC's taxi system, traditionally serving pre-arranged trips through livery cars and black cars. These vehicles cater to passengers seeking more personalized service than standard street-hail taxis, particularly in outer boroughs

and less-trafficked areas. However, the early 2010s ushered in a transformative era with the rise of app-based ride-hailing platforms like Uber and Lyft, fundamentally altering urban mobility dynamics.

Unlike traditional taxis, FHV's operate using app-based algorithms to calculate fares dynamically based on factors such as real-time demand, traffic conditions, and driver availability. This shift introduced innovative features like upfront fare estimation, GPS-based route optimization, and cashless payments, providing a seamless experience for passengers. Additionally, ride-hailing platforms diversified service offerings, including premium options like Uber Black and shared rides, expanding accessibility across different income levels and travel preferences.

4. Methodology and Findings

This thesis employs a multidisciplinary methodology combining descriptive analysis, modeling techniques, and comparative methods to explore urban mobility patterns and fare elasticity across various transportation modes. The methods were selected to address different facets of the research, ranging from analyzing spatial and temporal trends to quantifying the impacts of operational and contextual factors on urban transportation systems.

Descriptive Analysis

Descriptive methods served as the foundation for analyzing and visualizing trends across datasets, offering insights into spatial, temporal, and demographic patterns relevant to transportation systems. These methods were applied universally across all research components to provide a coherent understanding of the underlying data.

Temporal analyses involved exploring trends in trip volume, duration, and distance across different times of the day and week. Spatial patterns were analyzed using geospatial mapping techniques, which visualized the distribution of trips across pickup and drop-off zones, emphasizing regional differences in service utilization.

While these methods were broadly applied, some descriptive techniques were tailored to specific analyses. For example, demographic and geographic factors were integrated into the analysis using supplementary datasets, such as census data and public transportation accessibility measures. Population density and transit accessibility metrics were spatially matched to transportation data, providing additional context for understanding demand and supply distributions across urban areas.

Modeling Techniques

Statistical and computational models were employed to quantify relationships between variables and assess transportation dynamics. These models offered insights into factors driving demand, pricing, and mobility patterns across multiple modes of urban transit.

Ordinary Least Squares (OLS) Regression

OLS regression was a common tool applied across multiple research components to identify the factors influencing trip characteristics and fares. Common independent variables included trip distance, duration, traffic conditions, temporal indicators (e.g., weekends and rush hours), and location-based attributes. These models established baseline relationships, allowing for comparisons between modes such as buses, ride-hailing services, and traditional taxis.

Fixed Effects Models

To account for unobserved heterogeneity in spatial and operational characteristics, fixed-effects (FE) models were utilized. These models incorporated fixed effects for locations, such as pickup or drop-off zones, to control for location-specific influences while isolating the impact of demand factors like congestion and time of day. FE models were particularly useful in identifying how urban density and geographic variations shaped pricing and demand responsiveness across transportation systems.

Cluster-Based Analyses

K-means clustering was used to segment locations into categories based on shared characteristics, such as urban density or transit accessibility. This approach provided a more granular understanding of transportation patterns by grouping zones into clusters, such as high-density pickup to low-density drop-off areas, allowing for detailed insights into fare and demand variations across different urban contexts.

Together, these approaches provided a holistic view of urban mobility, capturing both the shared and distinct characteristics of fixed and dynamic pricing systems.

5. Dynamic vs. Fixed Pricing in Urban Mobility: An Empirical Analysis of Fare

Sensitivity in Taxi Services

5.1 Introduction

Urban transportation systems have experienced significant changes with the rise of digital ride-hailing platforms. These services, which use dynamic pricing algorithms that adjust fares based on real-time demand and supply conditions, differ from the fixed pricing models traditionally used by taxis. While both models calculate fares per mile and per minute, dynamic pricing, such as Uber's, incorporates surge pricing that increases fares during high-demand periods, whereas traditional taxi fares remain constant, relying on a metered system based on speed and distance. This shift has raised important questions about how these pricing models influence urban mobility, particularly in complex and densely populated cities like New York City.

Previous research has examined the mechanisms and effects of dynamic pricing, highlighting its role in optimizing resource allocation and encouraging driver availability during high-demand periods (Zha et al., 2018; Daganzo et al., 2019). However, these benefits often come with challenges, such as fare surges that disproportionately affect passengers during peak times. Studies have also noted the limitations of fixed pricing models, which can lead to inefficiencies in addressing varying demand across different times and locations. Despite these insights, there is a lack of direct comparative analysis between dynamic and fixed pricing systems, particularly in terms of their sensitivity to spatial and temporal factors such as traffic, trip timing, and population density.

This thesis seeks to fill this gap by investigating how dynamic and fixed pricing models respond to these factors, focusing on Uber's dynamic pricing system and the fixed pricing of Green Taxis in New York City. The central research question is: How do dynamic and fixed pricing models differ in their sensitivity to spatial and temporal demand factors, such as traffic, trip

timing, and area density? Two hypotheses are tested: (1) dynamic pricing models exhibit greater sensitivity to demand-based factors, including traffic and weekend patterns, and (2) dynamic pricing fares are more spatially flexible, with fares decreasing in high-density areas compared to low-density areas.

Using data from New York City's Taxi and Limousine Commission for March 2022, the study analyzes approximately 60,000 Green Taxi trips and 3.4 million Uber trips. Through statistical methods, including Ordinary Least Squares regression, fixed-effects models, and cluster-based analysis, the results reveal clear differences between the two pricing systems. Dynamic pricing is shown to respond more effectively to temporal fluctuations, such as rush hours and weekends, while also demonstrating adaptive spatial adjustments, particularly in high-density areas. Fixed pricing, by contrast, remains more rigid, with fares primarily determined by trip distance and duration.

These findings emphasize the flexibility of dynamic pricing in addressing urban mobility challenges, such as congestion and uneven demand, while highlighting the limitations of fixed pricing in adapting to these conditions. By offering a comparative analysis of these two systems, this research contributes to a deeper understanding of pricing strategies in urban transportation and provides insights for policymakers seeking to improve the efficiency and equity of mobility services.

5.2 Literature Review

Ride-sourcing platforms like Uber and Lyft employ dynamic pricing algorithms that adjust fares based on real-time demand density, traffic conditions, and temporal factors such as weekends and rush hours. This model aligns pricing more closely with supply-demand principles and addresses immediate urban mobility challenges by optimizing fleet utilization. As outlined by Zha et al. (2018), spatial and temporal pricing differentiation enables platforms

to clear markets efficiently by redistributing supply across underutilized zones and incentivizing driver availability during peak times. However, these benefits come with trade-offs, as customers may experience substantial fare surges even in scenarios where driver availability is adequate. Such drawbacks emphasize the need for geographically adaptive pricing strategies to enhance equitable service delivery.

Further, Daganzo et al. (2019) developed a comprehensive framework for modeling demand-responsive transportation services, encompassing traditional taxis, ride-hailing, and ridesharing. Their work highlights the trade-offs between passenger convenience, operational costs, and market efficiency. Dynamic pricing not only incentivizes higher vehicle occupancy but also optimizes resource allocation during peak demand. These insights underscore how advanced pricing models could inform sustainable urban mobility policies by balancing service quality and efficiency.

The role of labor supply responsiveness in dynamic pricing systems was explored by Zha et al. (2017), who found that while surge pricing increases driver availability during peak times, it can also lead to clustering of supply in high-demand areas, leaving other regions underserved. This dynamic highlights the need for geographically nuanced algorithms that consider not only real-time demand but also equitable distribution of rides across urban areas.

Demand elasticity, a central theme in dynamic pricing, reflects how fare adjustments influence passenger behavior. Wang et al. (2016) demonstrated that dynamic pricing stabilizes supply-demand equilibrium by aligning fares with consumers' willingness to pay, particularly during high-demand periods in densely populated areas. This supports the notion that dynamic pricing encourages passengers to modify their travel behavior, promoting trips during off-peak hours or to less congested zones, thereby reducing strain on urban transit systems.

Spatial factors also play a critical role in urban mobility. Yu et al. (2019) illustrates that the built environment, including population density, land use, and transit accessibility, significantly

influences ride-sourcing demand. Their findings highlight the importance of incorporating spatial variability into pricing models, reinforcing the utility of Uber's dynamic system in optimizing fleet utilization. Similarly, Safikhani et al. (2020) applied STAR models to capture spatio-temporal variations in taxi demand, emphasizing the potential of data-driven frameworks to adapt pricing mechanisms in response to real-time urban dynamics.

While dynamic pricing adapts efficiently to demand fluctuations, its implementation must address issues of equity and affordability. Fixed pricing models, such as those used by Green Taxis in New York City, offer fare stability and predictability but may fail to account for fluctuating urban mobility needs. This research builds on prior work by offering an empirical analysis of fare sensitivity to spatial and temporal demand factors, bridging the gap between dynamic and fixed pricing models.

Research Question

How do dynamic and fixed pricing models differ in their sensitivity to spatial and temporal demand factors, such as traffic, trip timing, and area density?

Hypotheses

Wang et al. (2016) highlight that dynamic pricing system aligns fares with demand fluctuations, particularly during high-demand periods, stabilizing supply-demand equilibrium. This adaptability contrasts with fixed pricing models, which remain static regardless of demand changes. Therefore, we hypothesize,

H1: Uber fares demonstrate stronger upward adjustments during weekends compared to Green Taxi fares.

H2: Uber fares demonstrate stronger upward adjustments during rush hours compared to Green Taxi fares.

Zha et al. (2018) and Yu et al. (2019) demonstrate that spatially adaptive pricing strategies, such as those used by ride-sourcing platforms, can redistribute supply and ensure balanced service coverage in densely populated zones. Therefore, we hypothesize,

H3: Uber pricing demonstrates greater spatial flexibility compared to Green taxi pricing.

H4: In high-density areas, Uber's dynamic fares exhibit a stronger response to real-time factors compared to low-density areas, supporting balanced service coverage.

5.3 Data Discovery

Data Sources

The primary data sources for this study comprise two comprehensive datasets obtained from New York City's Taxi and Limousine Commission (TLC) for March 2022, covering both Green Taxi and Uber trips. These datasets enable a comparative analysis of traditional models and dynamic pricing strategies within NYC's complex urban mobility framework. March 2022 was selected as a period marked by stable demand recovery post-COVID-19, making it a suitable month for analyzing fare dynamics and travel behavior.

The Green Taxi dataset, totaling approximately 60,000 records, reflects a fixed-pricing model regulated by the TLC. The Uber dataset consists of around 3.4 million records. Both datasets include variables such as pick-up and drop-off locations, trip distances, tips, and additional fees. Uber's fares are dynamically adjusted in real-time based on multiple demand factors, including time of day, location, and trip duration, with surge pricing algorithms that increase fares during peak demand periods. Unlike Green Taxis, which charge different rates for cruising versus stop-and-go traffic based on speed, Uber's pricing does not distinguish between traffic types but adjusts fares to reflect demand density and expected wait times when supply is limited.

The variance in pricing strategies between these two datasets allows for an empirical examination of how fixed and dynamic pricing models respond to spatial and temporal factors.

Uber's adaptive pricing model offers a framework to assess its efficacy in addressing supply-demand imbalances in high-demand urban environments, contrasting with the more rigid pricing structure of Green Taxis. To enhance the primary datasets, supplementary data from NYC Open Data and census resources provided critical information on population density and spatial attributes necessary for location-based analysis.

- The NYC Taxi Zones dataset, established by the Taxi and Limousine Commission, defines 265 distinct zones across New York City. Provided in shape file format (".shp" with associated metadata files), this dataset serves as a standardized spatial framework, facilitating the analysis of fixed location-based effects on fare and demand variations within urban neighborhoods.
- The 2020 Census Blocks dataset from the NYC Department of City Planning, comprising approximately 30,000 census blocks with demographic data, was used to calculate population density within each taxi zone. Geographic coordinates were obtained from NYC census metadata resources, enabling a precise spatial overlay and integration with taxi zones.

Data Preprocessing

1. Data Cleaning and Filtering

Initial preprocessing involved the removal of missing values and trips with abnormal durations or outlier fares to ensure data consistency. Specifically, trips with exceptionally short or long durations were excluded, as were fares that deviated significantly from expected ranges. Two primary fare-related filters were applied:

- Negative fare amounts: Records with negative fare values were discarded, as these likely indicate data errors.

- High fare outliers: To prevent skewed results, the top 1% of fares—representing trips with unusually long distances or exceptional circumstances—were excluded from further analysis.

Green Taxi trips, which averaged a fare of \$13.75, were primarily concentrated in Manhattan (56%) and Queens (22%). Unlike Uber, Green Taxi operates on a fixed pricing model regulated by the TLC, with rides predominantly originating from street hails within the Boro Zone—specific zones in NYC designated for Green Taxis. In contrast, Uber’s pricing model recorded an average fare of \$19.34, with trips exhibiting a broader geographic distribution: 42% of trips originated in Brooklyn and 26% in Queens. To ensure comparability between datasets, Uber trips were filtered by location ID to include only trips within the Boro Zone areas.

Approximately 12% of Uber trips included a congestion surcharge, whereas Green Taxis had a 75% rate of congestion surcharge application, highlighting differences in how traffic influences fare structures. The congestion surcharge, a flat fee introduced by the NYC Taxi and Limousine Commission (TLC) to mitigate traffic congestion below 96th Street in Manhattan, was uniformly applied to both Green Taxi and Uber rides. However, this surcharge differs in impact across pricing models: for Green Taxis, it functions as a static, location-based fee, while for Uber’s dynamic model, it acts alongside other real-time fare adjustments based on demand and traffic conditions, reflecting the immediate demand environment more directly.

2. Merging and Matching Geographical Data

To accurately align population density data with taxi trip data, a structured spatial preprocessing approach was implemented to integrate census blocks and taxi zones within a unified geographic framework. The EPSG:2263 NAD83 / New York Long Island (ftUS) projection, specifically suited for the New York City area, was selected to ensure consistency with local geographic standards.

The NYC Taxi Zones dataset, encompassing 265 defined zones, served as the foundational spatial layer for examining fare and demand variations, while the 2020 Census Blocks dataset, containing approximately 30,000 blocks with detailed demographic data, provided a high-resolution view of population density across the city. Through a spatial join operation, each census block was matched to its corresponding taxi zones. The overlay approach, illustrated in Figure 1, achieved a coherent mapping of census data onto taxi zones, ensuring that demographic influences on fare structures could be analyzed accurately across NYC's varied neighborhoods.

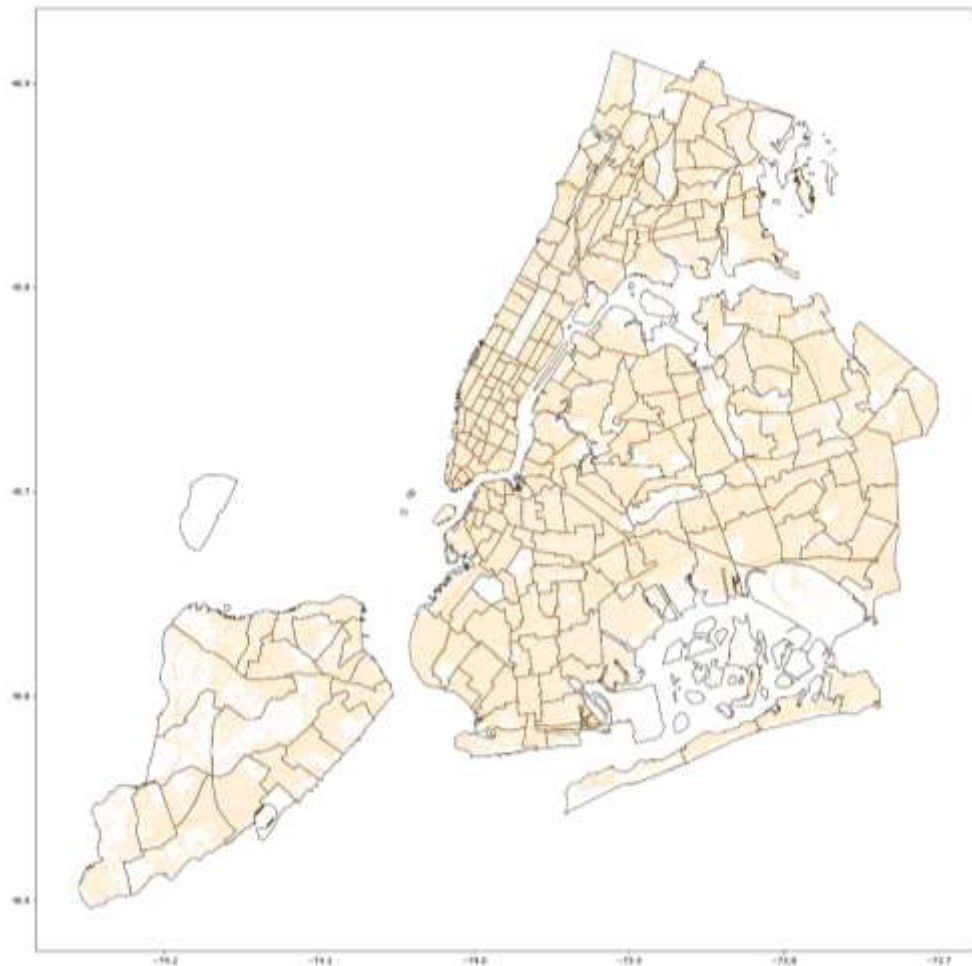


Figure 1. Taxi Zones and Census Blocks Boundaries

In cases where a census block overlapped multiple taxi zones, an additional step was necessary to ensure accurate allocation of population data. The population count for each overlapping block was divided proportionally among the intersecting zones, distributing a fraction of the

population to each zone based on the extent of overlap. Figures 2 and 3 illustrate the results of this alignment, showing the distribution of population density across both the more granular census blocks and the aggregated taxi zones. This approach enabled a refined population density calculation at the taxi zone level, enhancing the analysis of fare and demand patterns in relation to urban population characteristics.

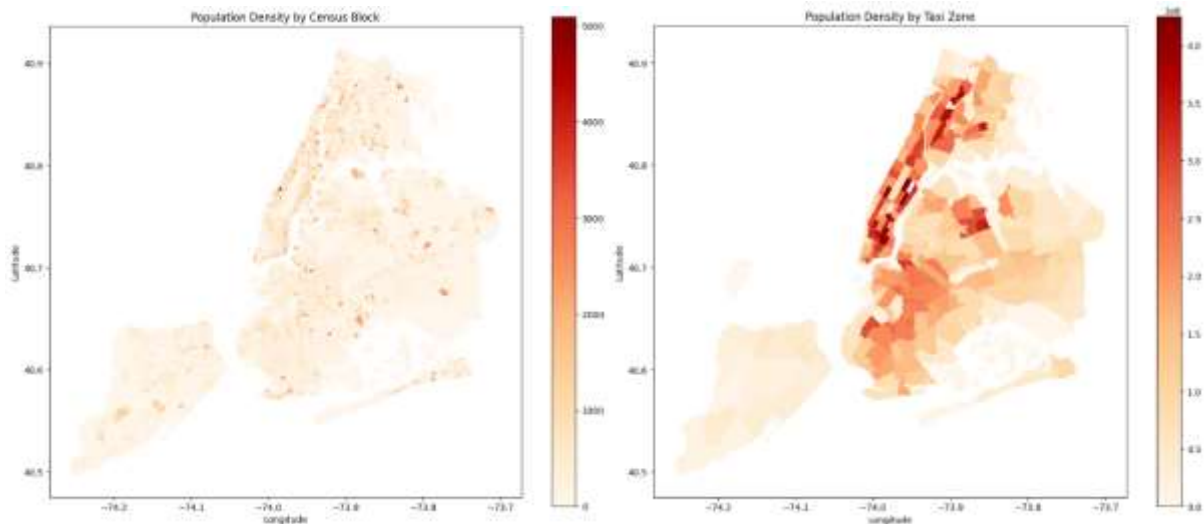


Figure 2 (left). Population Density by Census Block

Figure 3 (right). Population Density by Taxi Zone

3. Feature Engineering

To prepare the data for an in-depth comparative analysis of fare elasticity and demand responsiveness, several derived features were created:

- **Rush hour.** A binary “rush-hour” indicator was created to capture peak commute hours. A value of 1 denotes trips initiated between 7–9 AM or 5–7 PM, when travel demand is typically highest, and 0 for all other times.
- **Traffic.** The “traffic” variable was generated as a binary indicator based on the presence of a congestion surcharge. Trips with a congestion surcharge received a value of 1, reflecting increased traffic conditions, while trips without it received a 0.

- **Weekend indicator.** A “weekend” feature was created, marking trips that occurred on weekends with a 1 and those on weekdays with a 0.
- **Pickup and drop-off population density.** Population density was allocated to the dataset based on census block and taxi zone mappings developed in the spatial preprocessing stage.

5.4 Methodological Approaches

Ordinary Least Squares (OLS) Regression

To establish the baseline relationship between fare and trip characteristics across both pricing models, we applied Ordinary Least Squares (OLS) regression separately to the Green Taxi and Uber datasets. The regression model used trip characteristics—specifically, distance, duration, traffic, weekend, and rush hour indicators—as independent variables, with fare as the dependent variable. This approach allowed us to assess the foundational factors driving fares within each model, paying particular attention to how distance and time impact fares under fixed and dynamic pricing conditions.

The OLS model equation is specified as follows:

$$\begin{aligned} \text{Fare} = & \beta_0 + \beta_1 \cdot \text{Distance} + \beta_2 \cdot \text{Duration} + \beta_3 \cdot \text{Traffic} + \beta_4 \cdot \text{Weekend} \\ & + \beta_5 \cdot \text{Rush Hour} + \epsilon \end{aligned}$$

where:

- *Fare* is the dependent variable (base passenger fare),
- *Distance* and *Duration* are continuous variables representing trip distance and trip time, respectively,
- *Traffic*, *Weekend* and *Rush Hour* are binary indicators for congestion surcharge, weekend trips, and peak travel hours,
- ϵ represents the error term.

Fixed Effects (FE) Model

A Fixed Effects (FE) model was applied to analyze fare sensitivity in both Uber and Green Taxi datasets, using pickup or drop-off location as the fixed effect and including log-transformed drop-off population density as an independent variable. This approach controls for unobserved factors associated with specific pickup locations, isolating the impact of demand indicators such as traffic, weekend, and rush hour on fare sensitivity under dynamic and fixed pricing models. The purpose of this model is to test if Uber's dynamic pricing model remains sensitive to real-time demand factors when controlling for stable spatial effects of pickup locations.

The FE model equation is specified as follows:

$$\text{Fare} = \alpha + \gamma \text{Location} + \beta_1 \cdot \text{Distance} + \beta_2 \cdot \text{Duration} + \beta_3 \cdot \text{Traffic} + \beta_4 \cdot \text{Weekend} + \beta_5 \cdot \text{Rush Hour} + (\beta_6 \cdot \log(\text{Dropoff Population Density})) + \epsilon,$$

where:

- *Fare* represents the fare amount,
- $\gamma \text{Location}$ denotes fixed effects for each pickup/drop-off location,
- *Distance* and *Duration* capture the trip's distance and duration,
- *Traffic*, *Weekend*, and *Rush Hour* are demand indicators,
- $\log(\text{Dropoff Population Density})$ assesses the effect of density on fare adjustments,
- ϵ represents the error term.

K-Means Clustering

To examine how fare sensitivity to demand varies across different urban density zones, a cluster-based OLS regression was conducted. Rather than grouping trips by distance or volume categories alone, this analysis segmented locations into density-based clusters, each representing different urban demand patterns. By structuring the analysis around specific pickup (PU) and drop-off (DO) density pairings, it became possible to assess how Uber's fare

adjustments respond to a diverse array of urban environments, providing deeper insight into the dynamics of fare elasticity.

Each of the four clusters captures distinct combinations of PU and DO densities: “PU High Density to DO Low Density,” “PU Low Density to DO High Density,” “Medium-High Density Areas,” and “Superhigh Density Areas.” This segmentation enables a more nuanced understanding of how factors such as trip distance, duration, traffic, and rush hour impact fares across unique urban contexts, going beyond aggregate elasticity metrics to identify specific patterns within clustered zones.

5.5 Results

Fare Sensitivity to Trip Characteristics

The OLS regression presented in Table 1 reveals distinct fare sensitivity patterns between Uber’s dynamic model (1) and Green Taxi’s fixed pricing model (4). Both models incorporate trip distance and duration, but Uber’s fares are significantly more responsive to real-time conditions such as traffic, weekends, and rush hours.

Table 1. Regressions results comparison

	Green taxi trips			Uber taxi trips		
	(1)	(2)	(3)	(4)	(5)	(6)
const	2.57***	2.69***	4.39***	3.75***	4.24***	8.72***
Trip distance	1.95***	1.85***	1.86***	1.52***	1.52***	1.54***
Trip duration	0.32***	0.33***	0.33***	0.46***	0.45***	0.44***
Weekend	0,03	0.01	-0.01	0.49***	0.43***	0.38***
Traffic	-0.22***	0.03	0.09***	0.95***	-1.84***	0.80***
Rush hour	-0.17***	-0.13***	-0.10***	0.29***	0.30***	0.37***
Log DO Pop. Density			-0.10***			-0.26***
DO Location FE	No	Yes	No	No	Yes	No
PU Location FE	No	No	Yes	No	No	Yes
R ²	0.924	0.89	0.933	0.847	0.813	0.847
Observations	60922	61769	61769	3365508	3355399	3355399

*Coefficients indicate the impact of each variable, with *** $p < 0.01$, * $p < 0.05$, $p < 0.1$, and non-significant values showing no statistical effect.*

Uber fares increase by \$0.49 on weekends, in contrast to Green Taxi's results, where the weekend effect is statistically insignificant, suggesting that Uber's model actively adjusts to fluctuations in temporal demand. During congested periods, Uber's fares rise by \$0.95, while Green Taxis exhibit a fare decrease of \$0.22. This contrasting response suggests that Uber's dynamic model accommodates congestion as a premium condition, whereas Green Taxi fares may reflect shorter, intra-Manhattan trips, where the congestion surcharge applies. During rush hours, Uber's fares increase by \$0.29, while Green Taxis experience a slight decrease of \$0.17, highlighting a potential rigidity in Green Taxi's model or a unique intra-city demand pattern. Overall, these findings confirm Hypothesis 1 and 2, demonstrating that dynamic pricing, as used by Uber, exhibits heightened fare sensitivity to demand-driven factors, standing in stark contrast to Green Taxi's fixed pricing model.

Fare Sensitivity with Location-Based Controls

Applying a fixed-effects model with drop-off location as entity density fixed effect (Models 2 and 5 in Table 1) reveals notable differences in fare sensitivity between Green Taxi's fixed model and Uber's dynamic pricing. For Uber, fares increase by \$0.43 for weekends and \$0.30 for rush hours—consistent with OLS regression results, thereby reinforcing Uber's responsiveness to these demand conditions. Traffic, however, shows a significant negative coefficient of -\$1.84 under the fixed-effects model, compared to the positive coefficient in the OLS model. This shift likely reflects the nuanced role of Uber's congestion surcharge: while a flat fee applies under congestion (around \$2.50), Uber's dynamic adjustments may moderate overall fares in high-traffic scenarios to maintain appeal, resulting in the observed negative effect when accounting for location-based fixed effects.

In contrast, Green Taxi fares, unaffected by drop-off location due to the unknown destination

at pickup, show minimal responsiveness to external demand factors. Unlike Uber, weekend and traffic effects are statistically insignificant for Green Taxis, with only rush hour showing a slight negative effect of $-\$0.13$, suggesting a possible clustering of shorter trips during peak travel times, which affects the average fare structure.

These findings emphasize Uber's dynamic fare adjustments even within fixed spatial contexts, while Green Taxi fares remain more distance- and time-dependent, in line with their fixed pricing design.

Area Density Impact on Fares

Column 3 and 6 present the regression analysis with pick-up location as a fixed effect and demonstrates how drop-off population density influences fares for both Green Taxis (3) and Uber (6). For Uber, the coefficient for log-transformed drop-off population density is $-\$0.26$, meaning that for each 1% increase in drop-off population density, the fare is expected to decrease by approximately 0.26%. This suggests that Uber may lower fares in high-density areas, potentially reflecting an adaptive strategy to encourage trips in locations where the likelihood of nearby subsequent requests is higher.

In contrast, Green Taxi fares show a weaker negative association with drop-off density, with a coefficient of -0.10 . While statistically significant, this effect is less pronounced and could indicate that fares in high-density areas are modestly lower due to factors like shorter, intra-city routes rather than real-time fare adjustments. Additionally, this lower fare sensitivity in Green Taxis could also reflect compensation for the congestion surcharge observed in traffic conditions, as Green Taxis do not adjust for demand fluctuations in real-time. Non-significant weekend effect further underscores Green Taxis' lack of responsiveness to temporal demand shifts, unlike Uber's more dynamic adjustments.

In summary, these findings support Hypothesis 3, confirming that Uber's fares exhibit greater

responsiveness to area density than Green Taxis, reinforcing the adaptive advantage of dynamic pricing in high-demand locations.

Cluster-Based Fare Sensitivity Analysis Across Urban Density Zones

The fixed-effects analysis offered a broad perspective by treating population density as a continuous variable, showing that fares generally decrease in higher-density areas. This trend aligns with the hypothesis that Uber's dynamic pricing encourages demand in densely populated zones. However, interpreting density as a single variable limited insight into how fare responsiveness varies across distinct urban settings. The clustering approach then segmented locations into density-based categories presented at Figure 4, allowing for a more nuanced view of fare adjustments across different urban contexts. The cluster-based OLS regression (Table 2) reveals specific patterns in Uber's fare adaptation based on density.

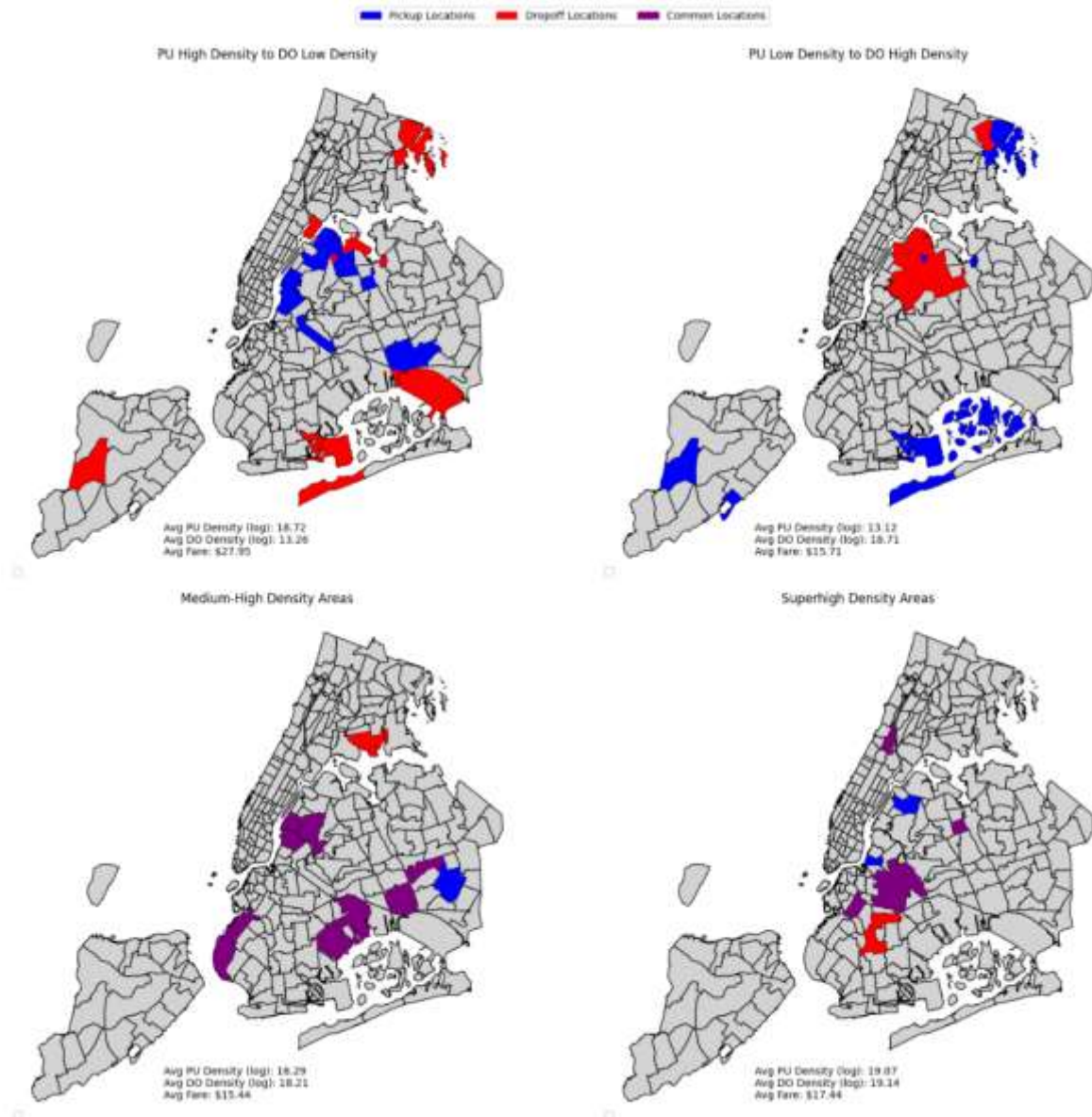


Figure 4. Clusters for PU and DO locations

Table 2. Regressions results for 4 PU&DO locations clustered

	PU High Density to DO Low Density	PU Low Density to DO High Density	Medium-High Density Areas	Superhigh Density Areas
const	2.59***	4.56***	3.69***	3.92***
Trip distance	1.80***	1.45***	1.46***	1.43***
Trip duration	0.48***	0.39***	0.46***	0.47***
Traffic	-5.48***	1.92***	1.26***	1.15***

Rush hour	0.84***	0.24**	0.20***	0.28***
Weekend	-0.27***	0.03	0.38***	0.62***
Same location	0.30	0.64	-0.09***	-0.18***
R ²	0.829	0.894	0.864	0.826
Observations	93955	5184	1102678	2135611

In "PU High Density to DO Low Density" clusters, fare sensitivity to distance is highest (coefficient 1.80), indicating that fares in high-demand pickup zones are especially distance-driven. This supports prior insights that Uber's model incentivizes longer trips in these zones to maintain demand. Conversely, in "PU Low Density to DO High Density" clusters, distance sensitivity remains but is more moderate (1.45), suggesting a balanced approach to fare increases, keeping trips to high-demand drop-off areas appealing without excessive premiums. Traffic effects show notable variance: in "PU High Density to DO Low Density" zones, traffic has a negative coefficient (-5.48), likely reflecting Uber's strategy to lower fares and retain demand under congestion. In "PU Low Density to DO High Density" zones, traffic results in fare increases (1.92), where congestion premiums likely support driver compensation in low-density areas.

Fare adjustments during rush hours also differ, with "PU High Density to DO Low Density" clusters showing the highest increase (0.84), underscoring the model's responsiveness to peak-time demand. The weekend effect is most pronounced in "Superhigh Density Areas" (0.62), suggesting that fares are adjusted to capture demand peaks when congestion is less restrictive. In summary, Hypothesis 4 is partially confirmed, as the analysis demonstrates a stronger response to most factors but not all. The fixed-effects regression revealed an overall density-driven trend in fare adjustments, while the clustering analysis provided further insights into how these adjustments vary across specific urban zones.

5.6 Discussions

This study addresses an existing gap in urban mobility research by directly comparing fixed and dynamic pricing models within New York City's taxi ecosystem, focusing on the nuanced fare adjustments to spatial and temporal demand. While previous research has explored dynamic pricing in isolation, this study's side-by-side analysis reveals distinct responses to demand shifts: Uber's fares are more sensitive to temporal demand factors—such as traffic, weekends, and rush hours—while Green Taxis display stability across these conditions. This aligns with prior research suggesting that dynamic pricing improves efficiency by balancing demand and supply in high-demand urban areas.

The clustering-based analysis adds a unique dimension and further extends these insights by revealing how fare elasticity varies across different density zones. High-density pickup zones show greater fare sensitivity to distance, while low-density zones apply traffic-based premiums to encourage trips. This approach enriches the fixed-effects analysis, providing insights into how Uber's pricing adapts to different urban contexts, offering potential applications for targeted fare-setting in high- and low-density areas alike.

5.7 Limitations and conclusion

The study's limitations include a dependence on fare and trip data, without metrics on driver behavior or acceptance rates, which could offer additional insights into the responsiveness of driver supply. Additionally, the clustering approach, while revealing density-based patterns, could benefit from further spatial granularity and consideration of external influences such as weather or special events.

In conclusion, this study contributes to urban mobility research by showcasing how dynamic pricing leverages data-driven adjustments to manage urban demand, contrasting with the inflexibility of fixed-pricing models. By optimizing fare adjustments in high-density zones and

moderating premiums during off-peak hours, dynamic pricing shows potential to enhance urban transportation. These insights into fare dynamics pave the way for further exploration of adaptive pricing's role in congestion management and transportation planning.

6. Conclusion

This study offers a comprehensive analysis of the diverse and interconnected facets of urban mobility in New York City, integrating findings across several research dimensions to address gaps in optimizing transportation systems. The analysis of mobility trends in NYC's outer boroughs illustrates the impact of Green Taxis and app-based services on transportation equity. The introduction of Green Taxis has improved access to underserved areas such as Brooklyn, Queens, and the Bronx. However, the findings reveal an uneven adoption across boroughs, with certain neighborhoods showing limited reliance on Green Taxis despite their availability. This outcome demonstrates the importance of targeted policies to enhance mobility equity, especially in areas with inconsistent service utilization.

The relationship between NYC's public bus system and taxi usage underscores a significant interplay between these two transportation modes. Enhanced bus services — measured through improved frequency, reduced delays, and increased geographic coverage — show a clear influence on reducing taxi demand, particularly in neighborhoods with improved transit accessibility. Notably, the findings reveal that enhanced bus services in densely populated areas like Brooklyn and Queens lead to a reduction in both Green and Yellow Taxi trips. This interaction shows the potential for integrated transportation policies to balance demand across public and private transit modes.

Investigations into the relationship between urban mobility dynamics and cost variability provide insights into spatial and temporal patterns of traditional taxi usage. The study highlights that Green and Yellow Taxis serve distinct geographic and demographic niches, with significant cost differences during specific hours, such as late nights and weekends. Geographically, Yellow Taxis dominate central Manhattan, where higher fares are often observed, while Green Taxis primarily serve outer boroughs with relatively stable fare patterns. This variability underscores the potential for adaptive pricing strategies to mitigate disparities and enhance fare

equity, especially in high-demand zones where pricing rigidity may disadvantage certain user groups.

The study on variability in taxi service usage uncovers distinct trip purposes and patterns between Green Taxis and ride-hailing platforms. Ride-hailing services are predominantly used for leisure-oriented, flexible travel during evenings and weekends, while Green Taxis are favored for routine, work-related commutes during weekdays. Spatial analysis indicates that ride-hailing services have broader geographic coverage, particularly in outer boroughs, whereas Green Taxis retain a strong presence in high-demand zones near transportation hubs. These findings highlight the complementary roles of these services as well as the importance of integrating adaptive pricing models to address varying user needs.

Finally, the analysis of fare sensitivity to pricing models offers a deeper understanding of how dynamic pricing adapts to demand fluctuations. The evaluation of dynamic versus fixed pricing models demonstrates significant differences in how each model responds to real-time demand. Dynamic pricing employed by ride-hailing platforms exhibits heightened fare sensitivity to traffic, rush hours, and weekend demand surges, effectively managing supply-demand imbalances. Conversely, Green Taxis' fixed pricing offers fare stability but lacks the adaptability to incentivize off-peak trips or mitigate congestion. Collectively, these findings demonstrate the interconnected nature of transit modes and highlight opportunities for policy integration. Enhanced bus services, adaptive pricing, and coordinated transit policies can create a more efficient, equitable, and responsive transportation system.

7. Resources

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