

AN ECONOMIC ANALYSIS OF THE
EFFECT OF UBER ON TAXI
MEDALLION VALUES

by

Maggie Kathleen O'Donnell

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ABSTRACT

Licensing requirements in taxi markets in the form of medallion systems are a common regulatory tool employed to regulate U.S. taxi industries. Such a system creates profits—i.e., rents—by restricting entry to the market. These profits are reflected in taxi medallion values, which are as high as \$1.32 million in New York City. Changes in demand for taxi services result in decreased profits and thus decreased medallion values. In this thesis, I measure the effect of the introduction and expansion of Uber, a ridesharing company, which causes a decrease in the demand for taxi services. Estimates of the aggregate losses to the taxi industry in each of the four cities range from \$387 million in Philadelphia to \$9.6 billion in NYC.

INTRODUCTION

Government regulation is ubiquitous in markets across the United States and throughout the world. Regulation utilizes a host of different policy tools that result in changes in output and price when the regulations are binding. Examples of regulatory policy tools include production quotas, restrictions on the allowable type and amount of inputs, and restrictions on entry into a regulated market. The introduction of regulation has far reaching effects on consumers, firms' input and output decisions, productivity, and quality. Most commonly throughout the different types of restrictions mentioned above, restrictions are found to result in changes in output. Production quotas have been employed for decades. The former U.S. federal tobacco program and California milk program, land restrictions on the planting of fruits and vegetables in the U.S., language requirements for manicurists, and licensing requirements in dentistry, all result in decreased output and increased prices (Brown et al. 2007, Rucker, Thurman, and Sumner 1995, Sumner and Wolf 1996, Lei et al. 2011, Federman et al. 2006, and Carroll and Gaston 1981). Alternatively, in the case of the former U.S. peanut program, production quotas coupled with support prices and import restrictions resulted in the same level of production as would be produced under free market conditions (Rucker and Thurman 1990). Production restrictions have also been shown to increase profits. In markets regulated by production quotas specifically, the profits are reflected in the value of the quotas (Brown et al. 2007, Thurman, and Sumner 1995, and Rucker and Thurman 1990).

Similar to production quotas, implementing licensing systems—which require firms to obtain a license to operate in the market—regulate markets. Examples of this

type of regulatory system are limited, but include taxi medallion systems and some states' liquor license systems. While limited work has been done to estimate the profits (or rents) associated with owning a liquor license and the determinants of those profits (Banovetz 2014), the size and determinants of rents associated with owning a taxi medallion have remained largely unexamined. This thesis examines the rents associated with owning a taxi medallion over time, the determinants of those rents, and the impact of Uber—a direct competitor to taxi services—on rents.

Taxicabs are an integral part of public transportation systems across the globe, particularly in major cities. The first motorized taxicab service in the United States dates back to 1896 with electric cabs in New York City (Kitch, Isaacson, and Kasper 1971). The regulation of taxicabs can be traced back to as early as the late 1920s in the United States. Limits on the number of taxis, mandated fare rates, and safety regulations have shielded the United States taxi industry from competition for nearly a century. Significant research has been devoted to understanding the implications of different types of regulation in the taxi industry. Numerous papers have analyzed the justification for regulation in the taxi industry and the effects of the various types regulatory systems employed throughout the United States on production, price, the creation of value in medallions, and taxi driver behavior (see Beesley 1973, Beesley and Glaister 1983, Cairns and Liston-Heyes 1996, DeVany 1975, Gallick and Siseck 1987, Kitch Isaacson, and Kasper 1971, Schaller 2007, and Schnieder 2010).

Protection from competition in taxi markets regulated by medallion systems has resulted in notably large and—until recently—increasing rents associated with owning a medallion. The value of a medallion reached a record high of nearly \$1.32 million in

New York City in May 2013.¹ The introduction of Uber and other ride sharing services has created the first major competitive threat to public transportation since the appearance of jitneys whose entry spurred the initial regulation of the taxi industry in the early 20th century. Using data from several thousand transfers of medallions, I estimate substantial declines in taxi medallion values due to the introduction and expansion of Uber in New York City, Chicago, Philadelphia, and Boston. Estimates suggest that in NYC, medallion values have decreased by over 68 percent and aggregate losses to the industry as a whole are nearly \$9.6 billion.

App based ridesharing companies—such as Uber, Lyft, and Sidecar—offer customers transportation hailed by using an app on their smartphone and provide simple, automatic, cash-free payment arrangement. Ridesharing companies have been found to be less expensive, faster, and more responsive to changing market conditions than traditional taxis (Nicholson 2014). While research has been conducted analyzing the effects of the ride-sharing industry on crime, traffic fatalities, arrests for driving under the influence, consumer welfare, and labor markets, little attention has been paid to its effect on the taxi industry (e.g., Dills and Mulholland 2017, Greenwood and Wattal 2015, Cohen et al. 2016, and Hall and Krueger 2016).

The effect of ride-sharing services on the taxi industry has yet to be empirically measured. This thesis measures the impact of Uber—the market leader in ride-sharing services—on the value of taxi medallions.² Studying four major U.S. cities that regulate the number of taxis using medallion systems, I find that the introduction and expansion of

¹ A transfer was completed in NYC in October 2015 for \$1.925 million under foreclosure but it is unclear how many medallions were transferred, thus it is not cited as the highest transfer price recorded.

² Rahel (2016) discusses the introduction of Uber to the taxi industry in New York City and provides predictions of its impacts on taxi medallion values, but lacks any empirical analysis.

Uber has resulted in significant decreases in the value of taxi medallions in each of the four cities. Estimates suggest the aggregate loss to each city's taxi industry range from roughly \$387 million for Philadelphia to \$9.6 billion for NYC. Compared to the annual consumer surplus gains in Uber's four largest cities estimated by Cohen et al. (2016), the annual losses in producer surplus as measured by the annualized decrease in medallion values is roughly a quarter of the size of the gains to consumer surplus.

In addition to estimating the loss in medallion values associated with Uber, this paper finds that medallion values respond to changes in economic conditions (e.g., the unemployment rate), changes in input costs (e.g., gasoline prices), and changes in the demand for taxi services (e.g., changes in population or the availability of substitutes). The loss incurred by the taxi industry from the introduction of Uber as a competitor may provides insights into other markets facing similar regulations. Market innovations such as Airbnb and microbreweries, which creatively avoid regulations in those markets, might have similar effects on the hotel industry and traditional bars and restaurants subject to liquor and/or beer and wine licenses.

BACKGROUND

The following chapter provides background information on taxi regulations and ride share services. The different types of regulatory systems employed across the United States are discussed. Following this discussion, the specific systems in each of the four cities analyzed in this thesis—NYC, Chicago, Boston, and Philadelphia—along with the history of those systems are explained in detail. Ride sharing services in general are then introduced and explained. Finally, the history of Uber and the services provided by Uber are examined.

Taxi Regulation

Taxi regulation in the United States grew in popularity during the early 1900s following the rise of personally owned automobiles across the nation, which lowered the barriers to entry into the taxi industry. There are two main theories of government regulation: public interest and capture. Public interest theory suggests that the purpose of regulation is to increase social welfare or—at the very least—benefit public interests in terms of quality, safety, ect. (Posner 1974). Alternatively, capture theory proposes that regulation is the result of lobbying by interest groups promoting their own interests (Posner 1974). As discussed further below, taxi companies often support entry regulation, suggesting that taxi regulations might be better explained under capture theory. Conversely, entry regulation—through fear of revocation—provides an incentive for taxi drivers and taxi owners to comply with safety regulations, which benefits the public by increasing the safety and quality of taxi services. This benefit to the public of improved

safety provides evidence that public interest theory, too, helps to explain taxi regulation. The two examples above suggest that both capture theory and public interest theory may be present in taxi regulation.

The taxi industry faces a slew of different types of regulation. Entry controls, fare mandates, lease rate limitations, and vehicle safety standards are commonly employed throughout the United States. Beesley (1973) identifies three main types of regulation in the taxi industry: monopoly rights, entry controls, and fare control. Monopoly rights, while not the focus of this thesis, are granted to a chosen taxi company (or companies) and they are the sole entity (or entities) allowed to operate taxis in the given region. Conversely, entry controls—in the form of medallion or permit systems—coupled with fare controls are present in all four of the cities studied in this paper.

A medallion system limits the number of taxis in operation in a specified area by requiring that all taxis display a medallion on the vehicle—usually a metal plate affixed to the hood of the taxi. A limited number of medallions are issued by the city, which, in turn, limits the number of taxis on the streets. In some cities, medallions can be sold or transferred from one owner to another and in others, they cannot. NYC, Chicago, Boston, and Philadelphia all allow for the transfer of medallions and collect sale data on the transfers. For this reason, these four cities are the cities used in this analysis. There are two main types of transfers of medallions, asset transfers and stock transfers. An asset transfer is the transfer of a medallion from one individual or corporation to another. A stock transfer is the transfer of stock in ownership of the medallion. Only asset transfers will be analyzed in this paper, as data on stock transfers are not available for Boston or Chicago and are limited in Philadelphia. A possible extension of this work would be to

incorporate the stock transfers along with asset transfers and explore possible heterogeneity in price between the two types of transfers.

New medallions are issued in regulated areas over time. These issuances commonly occur either through auctions, waiting in a queue of applications, or lotteries. An auction of new taxi medallions typically requires sealed bids to be submitted prior to the auction and awards the medallions to the highest bidders. In certain cities, new medallions are issued to individuals or corporations that have applied for a medallion once there is need by the city for more taxis. For example, if a city determines there is a public need for more taxis in a given region, they will issue additional medallions to individuals that have applied for a taxi medallion. Still other cities—for example Miami—allocate new medallions through a lottery. In this situation, prospective medallion owners enter the lottery and winners are drawn at random.

Fare regulation of taxis is quite common in the United States. Fares are typically regulated on a per mile basis and have set rates for idling or slow moving traffic. In addition, there is generally a flag drop fee—which is a base fare for simply picking up a passenger, airport fees, toll fees, and even sometimes peak hour fees and fuel surcharge fees. Taxis are required to be equipped with some sort of fare calculation device that incorporates all of the varying fees into the final fare amount. Fare rates differ across regions and across time. Fare rates have historically increased over time and added additional components (i.e., fuel surcharges).

Table 1: Taxi Fare Rates Across Cities

	NYC	Chicago	Philadelphia	Boston
<i>Base fare:</i>	\$2.50	\$3.25	\$2.47 ¹	\$2.20 ²
<i>Per mile charge:</i>	\$2.50	\$2.25	2.30	2.80
<i>Per minute charge:</i>	\$0.50	\$0.33	\$0.37	\$0.47
<i>Surcharge:</i>	\$0.30 ³	n/a	n/a	n/a
<i>Cost of five mile trip with five minutes of waiting time:</i>	\$17.80	\$16.17	\$15.82	\$18.55

Notes: All rates are as of March 2017. Per minute charges occur in slow-moving or stopped traffic. (1) Philadelphia base fare is \$2.70, but includes the first 1/10 mile traveled, \$0.23 (the cost of 1/10 miles traveled) is subtracted from this amount in the table for ease of comparison. (2) Boston's base fare is \$2.60 but includes the first 1/7 mile traveled, \$0.40 (the cost of 1/7 miles traveled) is subtracted from this amount in the table for ease of comparison. (3) NYC has a \$0.30 "Improvement Surcharge" for all trips.

Sources: TLC (2017), City of Chicago (2016), Philadelphia Parking Authority (2014), and Boston Police Department, n.d.

Taxi fare rates across the cities analyzed in this study are compared in table 1. Chicago exhibits the highest initial base fare of \$3.25 but the lowest per mile charge of \$2.25. For comparison, the cost a five-mile trip with five minutes of waiting time is calculated. The cost of the trip ranges from \$15.82 in Philadelphia to \$18.55 in Boston. In addition to being subject to regulated fare rates, many cities regulate the type of vehicles that can operate as taxis. Vehicles are frequently required to meet certain safety standards by being relatively new, going through safety inspections, and by complying with maximum mileage restrictions.

New York City

Although calls for entry controls by taxi company owners date back to at least 1929, regulation on the number of taxis in operation in New York City (NYC) officially began in 1937 with the Haas Act. The Act was implemented to remedy a perceived oversupply of taxicabs in the city. The excessive supply created reckless driving, traffic congestion, and intense competition between cab drivers (Van Gelder 1996 and Shreiber 1975). The act froze the number of taxicabs in 1937 by issuing medallions to any operating taxicab in the city at that time—resulting in 13,505 licenses being issued by the New York City government that year (Roistacher and White 1982). In addition to capping the number of taxis in the city, the act created two different types of medallions—independent and corporate medallions—and mandated a 60/40 ratio of corporate to independent medallions (2014 Taxicab Fact Book).

Independent medallions are medallions typically owned by the taxi driver himself and a single person cannot own more than one medallion at a time. The owner of an independent medallion earns income by operating a taxi and leasing their taxi to a second driver if they choose to do so. Corporate medallions—also known as fleet or mini-fleet medallions—are medallions that must be owned in quantities of two or more.³ Owners of corporate medallions lease out licensed vehicles to taxi drivers and collect a lease fee. Corporate medallions must be operated for at least two nine-hour shifts per day while independent medallions are free of these operation requirements (i.e., they can operate for as many or as few hours as they choose) (Roistacher and White 1982). Owners of corporate medallions typically preform the necessary maintenance on the vehicles (2014

³ There is no mention of an upper limit to the number of corporate medallions an individual or corporation can own.

Taxicab Fact Book). Roistacher and White (1982) describe the history of corporate medallions over time. Prior to the 1960s, only owners of large fleets of vehicles held corporate medallions. In the decades following, there was a rise of mini-feet operators. Mini-feet operators generally consist of two owners who operate only two taxis. In 1981, twenty large fleet owners held roughly 30 percent of corporate medallions, while the remaining 70 percent of corporate medallions were held by mini-fleet operators (Roistacher and White 1982).⁴

By the late 1940s, the number of taxis in New York City had decreased by roughly 1,700 medallions due to medallion owners failing to re-register their medallions or turning medallions into the city in response to low demand for taxis (Roistacher and White 1982). The number of medallions was capped by the City Council in 1971 at 11,787—where it remained until 1996 (Roistacher and White 1982). In 1996, there were two auctions of 133 medallions each and another in 1997 of 134 medallions. In the following years, there were auctions in 2004, 2006, 2007, 2008, 2013, and 2014, which increased the number of medallions in the city to where it currently remains at 13,333 medallions.

The Taxi and Limousine Commission (TLC) regulates taxis in NYC. The TLC sets fare rates, maximum lease rates, safety standards, taxi driver requirements, and monitors the sale of medallions. As mentioned above, fares are regulated in the city at a per mile and time rate with additional fees for tolls, airport trips, and surcharges for peak times (TLC, Taxicab Rate of Fare 2017). Fare rates as of 2017 are listed in table 1 and have increased over time and become more complex. Lease rates for fleet or mini-fleet

⁴ Of the 6,800 corporate medallions in circulation in 1982, fleet operators owned about 2,100 and 4,700 were owned by mini-fleet operators (Roistacher and White 1982).

vehicles are set by the TLC and cannot exceed the specified amount. Rates range from \$105-\$129 per 12 hour shift or \$630-\$737 per week, varying by day of the week and whether the shift is a day or a night shift (TLC Rules and Local Laws, Chapter 58 2017). The TLC also sets vehicle standards for taxis and has special requirements for prospective taxi drivers. Vehicles must pass tri-annual inspections, all equipment—such as brakes, tires, lights, seatbelts, and turning signals—must be in working order, and the vehicle must be clean on both the exterior and interior at all times during operation (TLC Rules and Local Laws, Chapter 58 2017).

Individuals seeking to become taxi drivers in NYC must be at least 19 years of age, have a valid Chauffeur's license, must be of sound mental and physical condition, be able to speak, read, write, and understand the English language, pass a drug test, and provide fingerprints among other requirements.⁵ In addition, applicants must complete a series of training programs: a defensive driving course, driver education training, and—when applicable—complete wheelchair passenger assistance training (TLC Rules and Local Laws, Chapter 80 2017).

Chicago

Chicago first introduced regulation limiting the number of taxis in operation in 1929. Taxi companies—the president of the largest taxi company in Chicago specifically—pushed for the entry controls (Kitch, Isaacson, and Kasper 1971). An ordinance limiting the number of taxis in Chicago was passed unanimously in by the City of Chicago 1929, but it was accidentally omitted from the Chicago Code of 1931 and was re-passed in April of 1932 (Kitch, Isaacson, and Kasper 1971). The entry limitations were

⁵ A licensed physician must certify the applicant's fitness (TLC Rules and Local Laws, Chapter 80 2017).

short-lived, however. In September 1932, the ordinance was repealed after public protest and allegations of taxi monopolies and complaints that Chicago's taxi rates were the highest among large U.S. cities (Kitch, Isaacson, and Kasper 1971). In 1934, entry controls were once again passed in Chicago with Municipal Code of Chicago (MCC) 9-112, which effectively limited the number of taxis to 4,166 (Frankena and Pautler, 1984). The number of active taxis has fluctuated over time in the city, decreasing to an estimated 3,000 from 1937-1951 and increasing thereafter to 6,999 in 2016 (Kitch, Isaacson, and Kasper 1971 and Nelson\Nygaard Consulting Associates Inc. 2014).⁶

Based from conversations with employees of the City of Chicago, the increase in the number of medallions over time appears to be from issuances by the city to individuals or companies that apply and from auctions of medallions held by the city. It appears there were two auctions of during the span of my data from 2007 to 2015. The auctions took place in 2010 and 2013. The 2010 auction sold ten individual medallions and 40 standard medallions while the 2013 auction attempted to auction 50 standard medallions. The 2015 auction failed to successfully auction any of the 50 medallions. Only one bidder participated in the auction and placed 30 bids for medallions. The bidder was unable to obtain funding for the 30 medallions and thus the auction failed to finalize the sale of any medallions. Similar to NYC, there are two types of medallions issued in Chicago—individual medallions and standard medallions.⁷ Individual medallions are medallions owned by taxi drivers who both own and operate the taxi and standard

⁶ The decrease of taxis in 1937 was a direct result of an agreement between a group of taxi drivers and the two largest taxi companies in Chicago at the time—Yellow Cab and Checker Cab—that resolved a driver strike that was currently occurring. The decrease in licenses and an increase in fare rates passed the City Council under the threat of another strike (Kitch, Isaacson, and Kasper 1971).

⁷ Chicago refers to individual medallions as “individual” medallions. For the sake of comparison between cities, I will refer to this type of medallion as an individual medallion.

medallions are owned by a corporation and are leased to drivers. Chicago's standard medallions are comparable to NYC's corporate medallions. Unlike most cities, Chicago does not issue medallions exclusively for use in wheelchair accessible taxis. Instead, they provide incentives for taxi owners to operate or lease wheelchair accessible taxis by offering lower medallion renewal fees, increased maximum lease rates for wheelchair accessible taxis, and mandating that at least 5 percent of taxis in fleets with over 20 medallions must be wheelchair accessible vehicles (MCC Section 9-112-570 2013). The City of Chicago regulates taxis and processes applications, renewals, auctions, and other regulatory nuances of the taxi industry. Chicago imposes maximum lease rates, annual renewal fees for medallions, vehicle and driver safety mandates, and fare regulations.⁸

Boston

Regulation of Boston taxis began with Chapter 392 of the Acts of 1930, which assigned the Police Commissioner of the City of Boston to regulate taxis and fare rates in Boston (*Boston Cab Dispatch, Inc. and EJT Management v. Uber Technology*, Mass. 2014). Legislation enabling the regulation of taxis was enacted to combat an excessive supply of taxis in Boston during the 1930s (Berdik 2004). The number of taxis was frozen at 1,525 in 1930 and remained there until the auction of 260 medallions in the 1990s (Berdik 2004).⁹ There are currently 1,825 licensed taxis in Boston, a number that has remained constant since at least 2004.¹⁰ The Hackney Carriage Unit of the Boston Police Department now heads regulation of taxis in Boston. The Unit does not appear to designate certain medallions for corporate or individual owners but does designate an

⁸ See Table 1 for fare rates in Chicago as of 2017.

⁹ The auction of 260 new medallions came after a ten-year legal battle (Berdik 2004).

¹⁰ As of February 2017, the number of medallions in Boston was still 1,825.

approved number of medallions to be used in wheelchair accessible vehicles (Boston Police Department, Rule 403 2008).

Boston also has set standards for vehicles and drivers. Vehicles have many requirements they must meet to function as a taxi. For example, vehicles cannot be more than six years old, they must be equipped with credit card processing devices, and they must pass periodic vehicle inspections (Boston Police Department, Rule 403 2008).

Drivers must obtain a Hackney Carriage Driver's License to legally operate a taxicab. An individual must apply for a license from the Hackney Carriage Unit and meet certain stipulations to successfully apply. Among a number of other requirements, applicants must be at least 21 years of age, pass an exam testing English speaking, writing, and understanding, have a valid Massachusetts drivers license, and possess a clean driving record (Boston Police Department, Rule 403 2008).

Taxi fares and leasing fees are also regulated in Boston. Fares are regulated on a per mile basis and by idling/waiting time and additional fees are charged for tolls and airport trips (Boston Police Department, Taxi Rates).¹¹ Maximum lease rates are set by the Unit and shift rates are broken down into 12 hour, 24 hour, weekly, and two-driver weekly segments (Boston Police Department, Rule 403 2008).

Philadelphia

Relatively less information on the history of taxi regulation in Philadelphia is available. Taxis in Philadelphia were regulated by the Pennsylvania Public Utilities Commission until 2004, when regulation was taken over by the Philadelphia Parking Authority (PPA). While it appears that there was entry control through certificates of

¹¹ See Table 1 for fare rates as of 2017.

public convenience prior to 1990, the medallion system currently in place began in July 1990 (Pennsylvania Code Title 52, Chapter 30 n.d.). Certificates of public convenience are issued by a city when there is demonstrated need for a particular service in a given area or city. During the transition to the medallion system, holders of certificates of public convenience for taxis were instructed to apply for medallions. Once their application was accepted a metal plate was issued and affixed to the hood of the taxi. It appears that additional medallions were issued over time through an application process and, in later years, through auctions conducted by the PPA. There is no evidence that Philadelphia distinguishes between corporate medallions and independent medallions as some other cities do. Recently, Philadelphia issued their first strictly wheelchair accessible medallions in a series of auctions from May 2015 through July 2015, in which 50 new wheelchair accessible medallions were auctioned.¹²

The auction system used by the PPA in the 2015 auctions is peculiar when compared to the auction systems of the other cities in this analysis. In New York City and Chicago, bidders in an auction submit sealed bids with the bid amount, contact information, and a check with a down payment. Then, the highest bidders receive the medallions auctioned. In Philadelphia, bidders were required to specify which medallion they were bidding for by including the medallion number on their sealed bid. This practice resulted in some higher bids becoming non-winning bids solely due to the medallion specified on the bid.¹³

¹² Although 50 medallions were put up for auction, only 30 were successfully sold. Twenty of the medallions did not reach settlement. The issues with reaching settlement are unknown (phone interview with PPA employee, Carrie Harris 2015).

¹³ The overall loss in revenue due to this practice is calculated to be \$16,011.00 based on the winning and non-winning bids from the auctions obtained from the PPA.

Philadelphia has similar regulations for fares, vehicle and driver standards, and medallion renewals as the other three other cities in this analysis. Fares are regulated in a combination of miles driven and time spent idling. Additional fees are added to the fare if trips are to or from the airport, if the trip requires passing through tolls, or if there is a fuel surcharge in effect (Philadelphia Parking Authority 2014).¹⁴ Taxicabs must be no more than eight years old or have more than 350,000 miles on the odometer at the time of operation and taxi drivers must hold a Public Utilities Commission Driver's Certificate. To obtain a Driver's Certificate, an individual must apply and meet driver history, age, proficient English speaking, and physical fitness requirements among other qualifications (Philadelphia Parking Authority-Taxicab and Limousine Regulations 2011). Taxi medallions and Driver's Certificates are required to be renewed annually through the PPA (Philadelphia Parking Authority – Medallion Renewal Form 2017).

Ridesharing

Ridesharing is a service that connects drivers and riders at the touch of a finger through the use of a smartphone application and the driver and rider's GPS locations. The leading rideshare companies are Uber and Lyft. While both offer similar products, Uber dominates the market. In a 2014 study using U.S. credit and debit card data, Uber's revenue was estimated to be roughly 12 times higher than Lyft's. The study also found Uber has a higher rate of growth than Lyft, provides more rides, and has a lower average cost per ride (Nicholson 2014).¹⁵ For this reason and a lack of data on the number of Lyft

¹⁴ See Table 1 for fare rates as of 2017.

¹⁵ Uber was an estimated five times faster at gaining new customers, six times faster at providing rides, and had over ten times faster growth in revenue, when compared to Lyft (Nicholson, 2014).

drivers over time, this paper solely focuses on Uber but recognizes doing so overestimates the effect of Uber's presence on taxi medallion values as part of the effect is due to Lyft and other rideshare companies.

Uber

Uber is an app-based ridesharing service that connects customers to drivers using their smartphone. The San Francisco based company launched in June 2010 and is currently operating in over 500 cities worldwide—with operations in the United States being the largest of the countries it is present in (Uber 2017b). A customer simply opens the Uber app on their smartphone, enters the desired destination, and requests a ride.¹⁶ A driver can then accept the request, notify the customer of acceptance, and provide an estimated time of arrival. Once the ride is completed, payment is automatically processed through the credit/debit card connected to the customer's account on the Uber app, allowing for a cash-free exchange between the rider and driver.

Uber's "surge pricing" is designed to reduce waiting times during periods of increased demand. Surge pricing increases prices little by little to encourage drivers to operate during high volume times and to give riders the option of paying the higher price or waiting until the price has returned to its normal baseline (Uber, 2016). Potential riders are notified of surge pricing before requesting a ride—allowing them to make an informed decision.

Uber also offers different types of vehicles for passengers to choose from for transportation services including UberX, UberXL, and UberBLACK. According to Uber's website, an UberX is a casual, low cost option that seats one to four riders.

¹⁶ A customer can also see the estimated cost of their trip prior to requesting it.

UberXL vehicles are vans or SUVs that can seat one to six passengers and are the lowest cost option for a large number of passengers. UberBLACK vehicles are stylish and accompanied by a professional driver.¹⁷ Uber also offers vehicles tailored to specific city needs. For example, in ski towns, Uber offers UberSKI, which consists of vehicles equipped with gear racks to accommodate transportation to ski resorts in the area (Uber 2017c).

While Uber first launched in San Francisco in June of 2010, its rollout to other cities occurred over time. New York City was the first of the four cities studied that Uber entered, entering the market in May of 2011 (Uber, 2011b)—followed by Chicago in September 2011 (Uber, 2011a), Boston in October 2011 (Uber, 2011c), and finally Philadelphia in June 2012 (Uber, 2012). As demonstrated by Hall and Krueger (2016), the number of active drivers has grown at different rates across cities as well. Figure 1 is a replication of the data presented in Hall and Krueger’s (2016) work showing the number of active Uber drivers by city since June 2012.¹⁸ As the figure shows, New York City and Chicago exhibit higher growth and thus have more active drivers than Boston and Philadelphia.

¹⁷ Professional drivers are drivers that drive for car service or limousine service companies.

¹⁸ An active driver refers to an Uber driver-partner who has completed at least four trips in the given month (Hall and Krueger, 2016). The replication process is described in the data section below.

Figure 1: Number of Uber Drivers Over Time

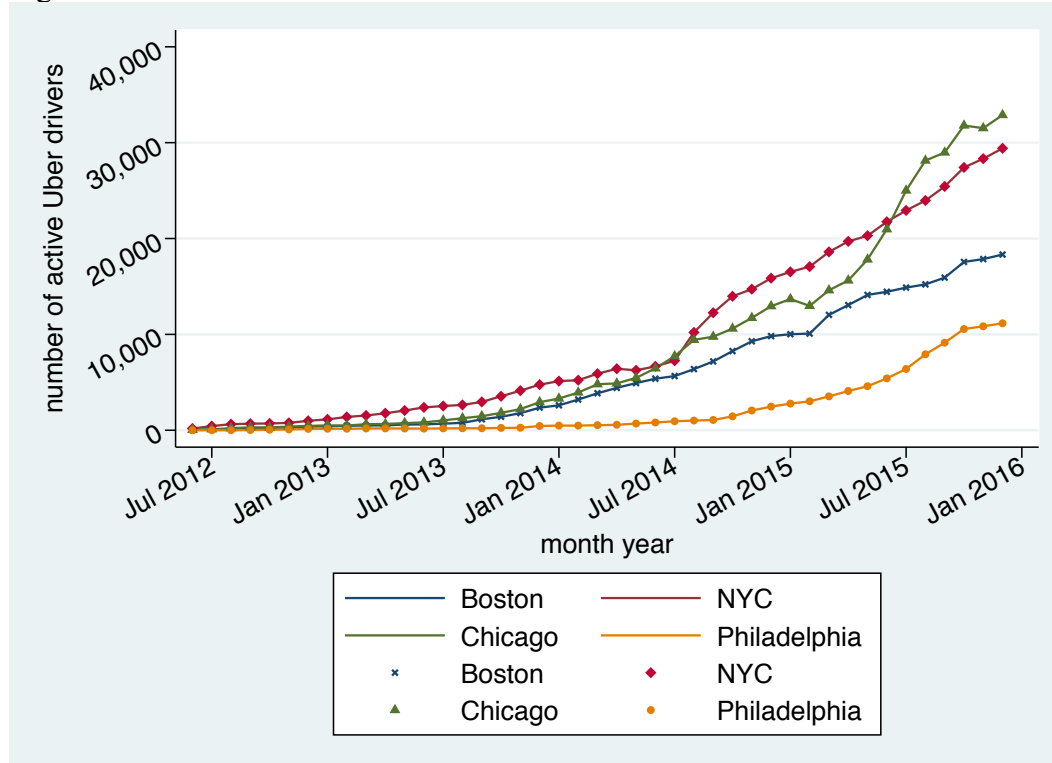


Figure 1 plots the number of Uber drivers in NYC, Chicago, Boston, and Philadelphia from June 2012 – December 2015. Source: Hall and Krueger (2016).

Over the span of its life, Uber has adapted different requirements one must meet to be become a driver partner in certain cities. Uber has done so to meet specific requirements set forth by officials in specific regions. It appears that concerns for passenger safety was a significant factor in the development of these new requirements (see Russo and BeBlasis 2016, and Conway and Reynolds 2016). Numerous incidents have been reported involving Uber drivers.¹⁹ BuzzFeed News leaked internal data that suggested Uber’s customer service team received nearly 12,000 complaint/feedback forms that mentioned the word “rape” or “sexual assault” over a two and a half year

¹⁹ See “Reported List of Incidents Involving Uber and Lyft.” *Who’s Driving You?* 2014-2015.

period (Sanchez 2016).²⁰ Uber has been criticized for failing to use fingerprint background checks—commonly required for prospective taxi drivers—and instead using background checks that check criminal records from the past seven years (Sanchez 2016). While some cities continue to allow Uber to use its own hiring policies, other cities have designed legislation requiring the company comply to with its requirements.

Independent of city specific regulations, prospective Uber driver partners must be at least 21 years of age, have at least one year of driving experience, a valid U.S. driver's license, and an eligible four-door vehicle that is registered and insured (Uber 2017a).²¹ Potential drivers then go through online screening, which includes a background check of their criminal history over the past seven years (Sanchez 2016). In NYC, prospective Uber drivers are now required to meet the same criteria as taxicab drivers. The requirements are those set forth by the TLC. Applicants must apply to be a “For-Hire-Driver” with the TLC, submit fingerprints for a background check, complete a defensive driving course, have a medical examination, and pass a drug test (Uber, License Requirements n.d.). Chicago requires Uber drivers to obtain a Chauffeur's license in addition to satisfying requirements set forth by Uber. Philadelphia and Boston do not appear to have any special requirements in place for Uber drivers. As mentioned above, safety concerns about Uber, and rideshare drivers in general, have been expressed through the media throughout the years. While no research has been done comparing the safety of Uber drivers—or rideshare drivers in general—to that of taxi drivers, it is an

²⁰ Uber representatives refuted the findings stating that the leaked information was “highly misleading” (Sanchez 2016).

²¹ Uber specifies age limits for vehicles that can be used. These limits differ across cities.

important factor in weighing the costs and benefits of the emergence of ridesharing into the transportation market.

RELATED LITERATURE

Taxi Regulatory Systems

The body of literature on taxi regulation is relatively limited. While some work has been done analyzing the need for and impact of the different types of regulation on the taxi industry, little has looked at the determinants of taxi medallion values or their response to changing market conditions. Gallick and Sisck (1987) theorize that the need for regulation in the taxi industry was created by technological change in automobiles that made them more easily obtainable to the general public. Once owning an automobile became more common, more people—particularly in metropolitan areas—began using their automobiles as taxis. These unlicensed taxis were known as jitneys. Enforcing average—i.e., regulated—pricing became difficult with the sudden increase in both taxis and jitneys.²² The medallion system was created to limit the number of taxis in operation and to abolish jitneys. The authors also discuss other types of regulation that help enforce average (i.e., regulated) pricing such as zoning, franchising, licensing, and bonding (Gallick and Sick 1987).

Cairns and Liston-Heyes (1996) find that regulation of price alone can lead to equilibrium, but it can also result in an oversupply of taxicabs. Regulating entry through a medallion system—if the number of medallions is set at or below the equilibrium quantity of taxis—in addition to price, is found to remedy the oversupply of taxis. Regulation is also found to create positive medallion values.²³ Two possible explanations of positive medallion values are given. The first assumes that profits generated by

²² Taxis were typically registered with a given city while jitneys were not registered in any way.

²³ This result is similar to the over supply of agriculture products under price support systems.

operating a taxi are greater than zero, and thus the license allowing one to operate a taxi is worth up to the amount of profits earned by doing so. The second views a medallion as a bond between the medallion owner and the regulatory authority. The bond prevents the medallion owner from failing to comply with regulations by threat of license revocation (Cairns and Liston-Heyes 1996). Medallions likely do act as bond between owners and regulatory agents, but positive hourly net revenues earned by drivers and strong opposition and legal battles being fought by taxi companies against Uber suggest that the taxi industry yields positive profits and the discounted value of these profits is reflected in medallion values (2014 Taxicab Fact Book 2014, Engquist 2015 and Taxi owners, lenders sue New York City over Uber 2015).

Schaller (2007) analyzes the effect of regulation in the taxi market by using a sample of 43 communities across the United States and Canada and exploiting variation in deregulation across communities and time. Consumers are found to increase reports of unsatisfactory services post deregulation and lack of regulation is found to result in an over supply of cabs, increases in uninsured and unlicensed cabs, high turnover in drivers, and low quality dispatch services. Deregulation appears to succeed in smaller cities that lack street hail and cab stand markets.

Considerable research has been conducted to analyze the need for and the effect of different types of regulation on production, price, and quality, but the determinants of taxi medallion values has remained largely unexamined in the literature. The exception to this assertion is a report done by Roistacher and White in 1982. The report thoroughly explains taxi regulation in NYC over time and develops predictions of the effects of eased entry with fare regulation, eased entry and eased fare regulation, and an increase in

the number of medallions issued. In addition, a regression analysis is conducted using monthly average transfer price data from 1964 to 1981 to estimate the determinants of taxi medallion values. Findings suggest that medallion prices reflect discounted expected taxicab profits and that basic economic factors such as the unemployment rate, the cost of substitutes—measured by subway fares—taxi fare rates, and the cost of operating a taxi, explain patterns in medallion prices over time. While Roistacher and White (1982) estimate the determinants of taxi medallion values in NYC, the analysis was conducted 35 years ago and it is unclear if their findings generalize to present day medallion values. This thesis appears to be the first analysis with a primary focus of analyzing taxi medallion values, their determinants, and the effect of Uber on those values.

Uber and Taxi Service Markets

Recently, significant research has been devoted to analyzing the effects of Uber on various outcomes. Dills and Mulholland (2017) find the introduction of Uber results in a decrease in fatal vehicle crashes, the rate of DUIs, and provides some evidence that Uber results in lower arrest rates for assault and disorderly conduct. Findings also suggest an increase in vehicle thefts associated with the introduction of Uber to a city (Dills and Mulholland 2017). Similarly, Greenwood and Wattal (2015) find that Uber decreases the number of alcohol related motor vehicle homicides in California cities.

Rahel (2016) hypothesizes the impact of Uber on the NYC taxi industry. The author speculates that protection provided by the medallion system created a disincentive for technological innovation in the taxi industry. Two policies are proposed to help correct issues associated with a medallion system. The first being the deregulation of the

number of taxis allowed to operate and the second to develop an app similar to the Uber app but for taxis.²⁴ While this paper thoroughly summarizes taxi regulation in NYC and theorizes the effect of Uber's entry to the taxi industry, it lacks any empirical analysis to confirm its theoretical predictions.

Cramer and Krueger (2016) compare the capacity utilization rate between UberX drivers and taxi drivers in five U.S. cities.²⁵ Capacity utilization rates are measured in two ways. First as the percentage of hours worked with a passenger in the vehicle, and then by the percentage of miles driven that a driver has a customer in the vehicle. Findings indicate that, on average, UberX drivers have capacity utilization rates 30 percent higher than taxi drivers. New York City, however, exhibits nearly identical capacity utilization rates for UberX and taxi drivers—a result attributed to NYC's high population density and the abundance of street hail demand in the city. Findings are suggested to be driven by increased efficiency in finding passengers and flexible pricing from the Uber app.

Two shortcomings of the paper are addressed. The first being that, while Uber drivers can choose when and for what duration they wish to work, taxi drivers are often required to work set shifts. Uber drivers might choose to only work in peak hours when they expect high capacity utilization rates, whereas taxi drivers may be forced work both in peak and slow periods—which would explain the differences in utilization rates. The authors attempt to control for this by comparing UberX utilization rates between drivers of shorter shifts and drivers of shifts similar to typical taxi drivers, but without controlling for day of week or time of day, there is still potential bias in the results. The second shortcoming arises from the unmatched time periods of the taxi and Uber driver

²⁴ Interestingly, Uber offers a service that matches taxi drivers to customers on its app already.

²⁵ The five cities analyzed are: Boston, Los Angeles, New York City, San Francisco, and Seattle.

data. Taxi driver utilization rates were calculated using data that was from the year prior to UberX driver utilization rates data. This potentially biases the author's findings toward zero as one might expect that as Uber gained popularity, it might have a negative effect of taxi driver utilization rates. An interesting question that the authors were unable to address due to data limitations is what happened to taxi driver utilization rates once Uber entered the market. While not explored in this paper, responses in taxi driver utilization rates due to the entrance of Uber is an interesting topic for future research.

Hall and Kruger (2016) analyze the labor market of Uber drivers. Uber drivers are found to be more similar to the general workforce than taxi drivers. In contrast to taxi drivers, many Uber partners drive only part-time. Rather than viewing driving for Uber as a career, driver partners are found to drive for Uber as a way to smooth fluctuations in their income. The number of active Uber drivers in the sample cities has grown rapidly from 2012 to 2016 and at an increasing rate. At the close of 2015, Los Angeles had the highest number of Uber drivers in the United States with nearly 60,000 active driver partners, followed by San Francisco and Chicago. The number of Uber drivers in a given city is found to be positively correlated with population and the number of taxi licenses per capita. The positive relationship is attributed to excess demand for ridesharing services in cities that have more taxis per capita. The number of Uber drivers in a city is found to be unrelated to the cost of a five-mile Uber ride in the city.

Cohen, Hahn, Hall, Levitt, and Metcalfe (2016) estimate the consumer surplus associated with Uber. By using unique data obtained directly from Uber app users, the demand for UberX and the associated consumer surplus in Uber's four biggest markets—Chicago, Los Angeles, New York City, and San Francisco is estimated. The data allow

the authors to trace consumer's decisions to request or not request rides during times of surge pricing to map out demand for UberX and to estimate the associated consumer surplus. The estimates are then extrapolated to the entire United States using UberX gross bookings. Demand is estimated to be inelastic—which they note is surprising given the abundance of substitutes for Uber like taxis, public transportation, etc. The consumer surplus generated by UberX is estimated to be \$2.88 billion in 2015 in the four sample cities and \$6.76 billion in the United States as a whole.

The literature summarized above examines various aspects of taxi regulation and outcomes related to the rise of ridesharing services. While the determinants of taxi medallion values have been analyzed, the analysis, which was based on a sample of monthly data, took place over 30 years ago and is in need of an update. Cohen et al. (2016) measure the benefits of UberX in terms of consumer surplus but nothing to-date appears to have been done to empirically measure the effect of Uber on taxi medallion values. This paper contributes to the literature by reviewing the taxi regulatory systems in four major cities across the United States, discussing and testing a theoretical model of the determinants of taxi medallion values, and, lastly, empirically measuring the impact of Uber on taxi medallion values and thus the taxi industry's profitability.

THEORETICAL FRAMEWORK

In this chapter, I develop a model of the regulation of taxi markets under a medallion system. Both graphical and mathematical components of the model are developed. The development of the model is comprised of three steps. The graphical component of the model is first developed allowing the price of taxi services to be flexible. The graphical model is then modified to incorporate the fixed pricing system in the taxi service industry. I then develop a mathematical model of medallion regulatory systems. The mathematical model yields comparative statics results that agree with predictions from the graphical models.

Graphical Analysis: Market Based Pricing

Figure 2: Three-Graph Framework Under Market Based Pricing: initial regulation

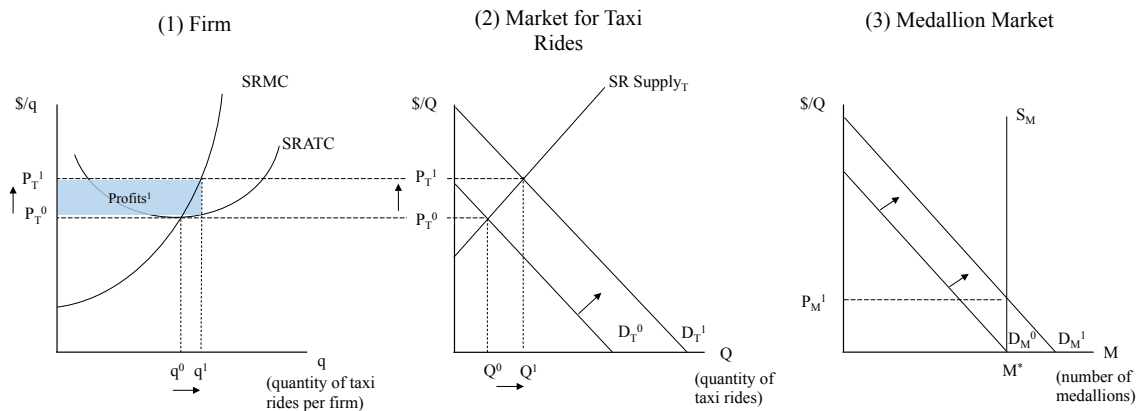


Figure 2 provides a graphical framework for the effects of restrictions on entry in the taxi industry in a one period model. This variation of the model allows the price of taxi rides to adjust in response to shifts in demand or supply. The first of the three graphs depicts a representative firm and its short run average total cost (SRATC) and short run

marginal cost (SRMC) functions. Arguments in these cost curves include the cost of gasoline, repair expenses, and search costs that occur when a driver cruises the streets seeking hail customers. The second graph illustrates the market for taxi rides. The third graph is the market for taxi medallions, i.e., licenses to operate taxis. Prior to restrictions on entry the three graphs are in the following equilibriums. Initially, the demand for taxi rides is represented by the D_T^0 curve. This curve represents the relationship between the cost of a taxi ride and the expected number of rides that will be demanded in a given period. Taxi drivers are assumed to be risk neutral in their decision of the quantity of rides to produce. SR Supply^T represents the supply of taxi rides—which is the horizontal summation of all the firms' short run marginal cost curves. The market clearing price and quantity are P_T^0 and Q^0 . At a price of P_T^0 , each firm provides q^0 rides. At P_T^0 and q^0 , SRATC is equal to SRMC and profits are zero. At this initial equilibrium, there are M^* firms in the market. M^* multiplied by q^0 is equal to the market quantity of Q^0 . M^* is the number of firms at which, all else equal, profits are zero. Given this zero profit condition, capping the number of taxis at M^* results in a willingness to pay for a medallion of zero dollars—which yields the horizontal intercept of D_M^0 , the demand for medallions shown in the third graph.

Capping the number of medallions creates a perfectly inelastic supply curve of medallions, represented here by S_M . This is similar to the situation that occurred when each city began regulating the number of taxis. Taxis currently in operation were allotted licenses, and, all else equal, there were no changes and profits remained zero. Limiting the number of medallions also changes the market supply curve of taxi rides. After a certain quantity, the supply of taxi rides becomes vertical because taxi drivers are at

capacity and cannot produce additional rides as the number of taxis is capped. In this analysis, I assume taxi drivers are operating on the upward sloping portion of the supply curve. In the third panel, D_M^0 is drawn as a linear function, although it could take numerous functional forms. The demand function is determined by the willingness to pay for a medallion, which, in a one period model, is the difference between the revenue from operating a taxi and the associated costs.²⁶ The demand for medallions, D_M^0 , is downward sloping by the Envelope Theorem. For example, suppose the supply of medallions decreases, which causes market supply to decrease and the equilibrium price of taxi rides to increase. The Envelope Theorem states the change in profits resulting from a change in price is equal to the supply curve, which is positive. Therefore, a decrease in the number of medallions (i.e., the supply of medallions) increases profits, and an increase in profits increases the willingness to pay for a medallion. Because the willingness to pay for a medallion increases when the supply of medallions decreases, the demand for medallions must be downward sloping.

Now, assume the demand for taxi rides increases but the number of medallions remains constant. Recall that after the initial regulations were implemented, many cities held the number of medallions constant even after the demand for taxis increased.²⁷ An increase in the demand for taxis shifts the demand in the market for taxi rides to D_T^1 . This increase in demand increases the equilibrium price of taxi rides to P_T^1 and the equilibrium quantity to Q^1 . Each firm in the industry now maximizes profits by producing q^1

²⁶ In a multiple period model, this would be the difference between expected revenues and expected costs.

²⁷ Recall that NYC is an exception. In the late 1940s, demand for taxis fell and some licenses were not renewed or were surrendered to the city, decreasing the number of medallions. After this decline in medallions, the number remained constant as demand for taxi services grew until the first auction of additional medallions was held in 1992.

services—where short-run marginal cost (SRMC) is equal to the market price of P_T^1 .

Profits are represented the Profits¹ shaded region in the representative firm graph. Each

firm earns profits equal to the difference between price, P_T^1 , and the short run average total cost of producing q^1 taxi services, multiplied by the quantity produced, q^1 . Once

firms earn positive profits, the demand for taxi medallions increases. Demand for

medallions increases until the equilibrium price of a medallion is equal to the profits

earned by operating a taxi. This price arises because an individual is willing to pay up to the amount of the profits earned by operating a taxi for the rights to operate a taxi.

Graphically, the demand for medallions increases to D_M^1 and the equilibrium price of a

medallion is P_M^1 , where P_M^1 is equal to the shaded Profits¹ region in the firm graph. This

model represents the taxi industry in NYC, Chicago, Boston, and Philadelphia prior to the

entrance of Uber. Positive and large transfer prices suggest that profits were sizeable for

taxi medallion owners during this period. This model is a one period model. In a multiple

period model, the price of a medallion would represent discounted expected future

profits.

Figure 3: Three-Graph Framework Under Market Based Pricing: effects of Uber's entrance

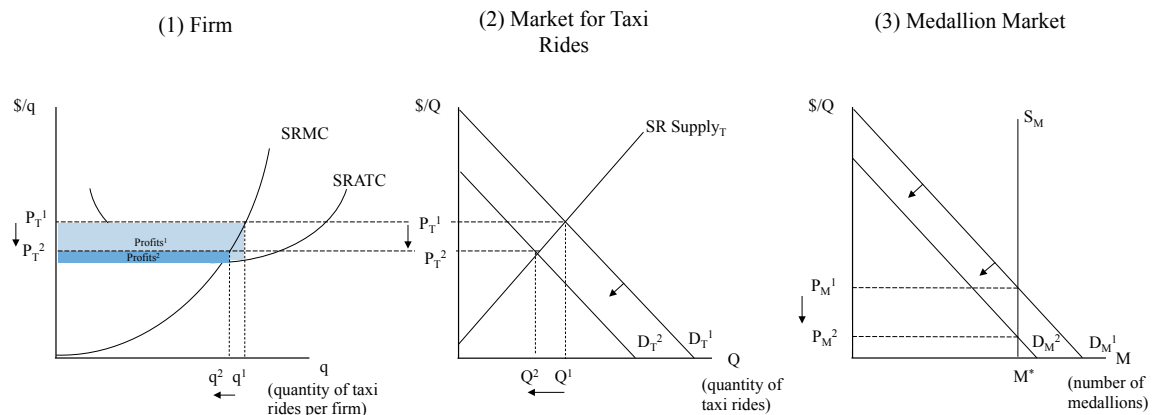


Figure 3 illustrates the effect of the entrance and expansion of Uber on the taxi industry. Initially, the second equilibrium from figure 2 is observed. Demand for taxi rides is represented by the D_T^1 curve, SR Supply_T represents the supply of taxi rides, and the equilibrium price and quantity of taxi rides are P_T^1 and Q^1 . Each firm maximizes profits by producing q^1 and the Profits¹ region represents firm profits. Demand for medallions is equal to D_M^1 and the market-clearing price for medallions is P_M^1 , which is also equal to the profits of owning one medallion—Profits¹.

Once Uber enters the market and gains a customer base, the demand for taxi rides falls to D_T^2 because Uber is viewed as a substitute for taxi services. This inward shift in demand decreases the equilibrium price to of taxi rides P_T^2 and quantity of taxi rides to Q^2 . Firms now maximize profits by producing q^2 , which is where short run marginal cost (SRMC) equals the new market price of P_T^2 . Profits decrease to the Profits² region. The reduction in profits decreases demand for medallions, shifting the demand for medallions to D_M^2 . The new market-clearing price for taxi medallions is P_M^2 —which is equal to the current profits earned by owning one medallion, Profits². The difference between P_M^1 and P_M^2 represents the decrease in medallion value due to the entrance and expansion of Uber. This model, however, does not account for the regulated fare rates for taxi services in many cities. Figures 4 and 5 illustrate models that incorporate these regulated fare rates. As will be demonstrated, theoretical predictions are consistent across the two models.

Graphical Analysis: Fixed Pricing

Figure 4: Three-Graph Framework Under Fixed Pricing: initial regulation

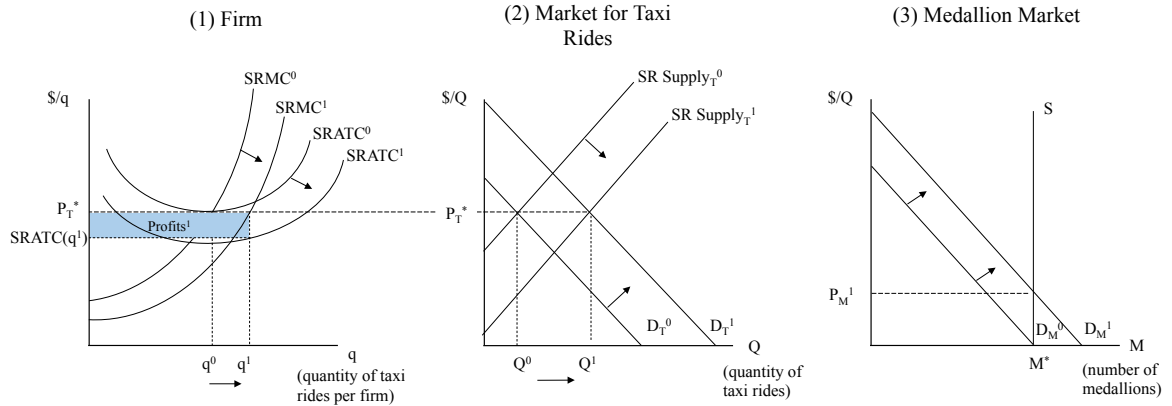


Figure 4 illustrates the impacts of regulation on the taxi industry while accounting for regulated fare rates. Regulated fare rates in the taxi industry are unique in that they do not act in a similar manner as price supports or price ceilings. Dependent on the demand and supply of taxi services, taxi fare rates can act as price supports or price ceilings. For example during times of high demand, there is a surplus of customers; here taxi fare rates act as a price ceiling. During times of either high demand or increased supply, there is a surplus of taxicabs; here taxi fare rates act as price support. This is an interesting finding and one that appears to be rare in regulated markets.

Graph 1, is, again, a representative firm in the taxi industry. The market for taxi rides is described in graph 2. Graph 3 shows the market for taxi medallions. The competitive market clearing price and quantity in the market for taxi rides are P_T^* and Q^0 . P_T^* is the fixed fare rate set by the regulatory agency. At a price of P_T^* , each firm provides q^0 rides. At P_T^* and q^0 , $SRATC^0$ is equal to $SRMC^0$ and thus profits are zero. Similar to figure 2, at this equilibrium, there are M^* firms in the market. M^* is the number

of firms at which, all else equal, profits are zero. Limiting the number of taxis at M^* results in a willingness to pay for a medallion or license of zero dollars, yielding the horizontal intercept of D_M^0 , the demand for medallions. As discussed in figure 2, this initial regulation describes a situation akin to that of the initial regulation on taxis in each of the sample cities. Demand for medallions is again assumed to be linear and downward sloping by the Envelope Theorem.

Then, assume demand for taxi rides increases to D_T^1 . Once this shift occurs, if the price of taxi rides is fixed at P_T^* , the quantity demanded is greater than quantity supplied, and taxi drivers spend less time cruising the streets looking for hail customers. Recall search costs of seeking passengers is an argument in the firms' cost function and thus the decrease in cruising decreases costs and shifts the short run average total cost curve to $SRATC^1$ and the short run marginal cost curve to $SRMC^1$. The outward shift in short run marginal cost creates an outward shift in the short run supply of taxi rides to $SR\text{ Supply}_T^1$ because the short run supply is the horizontal summation of all firms' short run marginal cost curves. Firms maximize profits by producing q^1 rides, which is where $SRMC^1$ equals the regulated price of P_T^* . There are still M^* taxis in the industry, each producing q^1 rides, which creates a market equilibrium quantity of Q^1 .²⁸ The decrease in cruising costs associated with increased demand but regulated fares and entry restrictions, creates positive profits. Profits are equal to the difference between the revenue of producing q^1 taxi rides and the costs of producing those rides. Graphically, the shaded region, labeled Profits^1 , represents profits under these market conditions. Profits^1 is equal to the area below the regulated price— P_T^* — and above the short run average total cost of producing

²⁸ Where $Q^1 = (M^*) \cdot (q^1)$

q^1 rides— $SRATC(q^1)$ —out to the quantity produced q^1 . Positive profits increase the demand for taxi medallions to D_M^1 , which increases the equilibrium price of a medallion to P_M^1 , where P_M^1 is equal to the shaded Profits¹ region.

Figure 5: Three-Graph Framework Under Fixed Pricing: effects of Uber's entrance

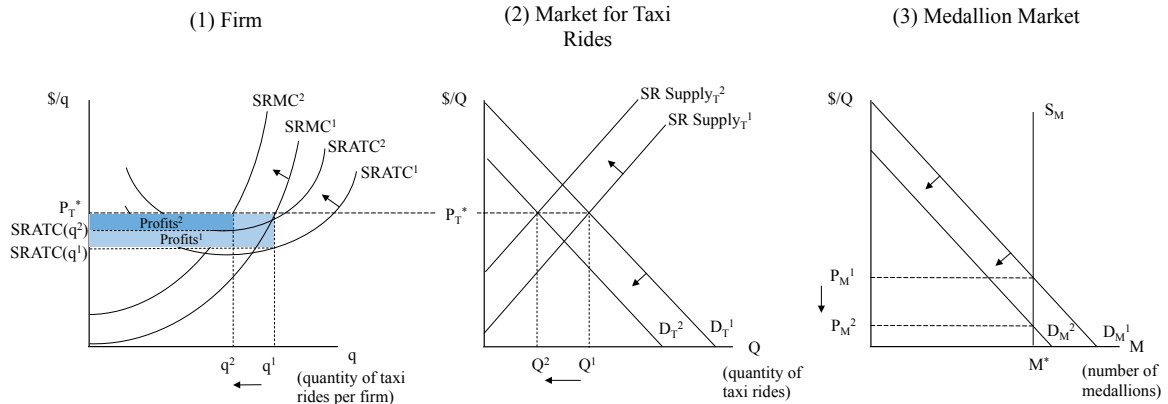


Figure 5 extends the analysis of figure 4 by analyzing the effect of a decrease in demand for taxi services caused by, for example, the entrance and expansion of Uber. Figure 5 begins where figure 4 ended. The market for taxi rides is in equilibrium with the regulated price of P_T^* and a quantity of Q^1 . D_T^1 is the demand for taxi rides and $SR Supply_T^1$ is the short run supply of taxi rides. Each firm produces q^1 rides and there are M^* firms—i.e., taxis—in the industry, each earning profits of $Profits^1$. The demand for taxi medallions is equal to D_M^1 , M^* is the supply of medallions, and the equilibrium price of a medallion is P_M^1 —which is equal to $Profits^1$.

Once Uber enters a city and establishes a customer base, demand for taxi rides falls, as Uber is a substitute for taxi rides. In the second graph of figure 5, demand for taxi rides decreases to D_T^2 . With the price of taxi services fixed at P_T^* , the decrease in demand for taxi rides results in quantity supplied being greater than quantity

demanded and it now becomes more time consuming—and thus costly—for taxi drivers to secure passengers. For example, the cost of gasoline used to search for passengers is now apart of the cost of the ride. Increases in time spent cruising streets looking for passengers increase both short run average total cost and short run marginal cost for each firm because each ride secured now has the incurred search costs incorporated in the cost of the ride to the driver. Short run average total cost increases from $SRATC^1$ to $SRATC^2$ and short run marginal cost increases from $SRMC^1$ to $SRMC^2$. The increase in short run marginal cost decreases the short run supply of taxi rides because the short run market supply of taxi rides is simple the horizontal summation of all firms' short run marginal cost curves above the minimum of short run average variable cost. Short run supply decreases from $SR\text{ Supply}_T^1$ to $SR\text{ Supply}_T^2$.

The new observed equilibrium in the market for taxi rides is the regulated price of P_T^* and a quantity of Q^2 . At the price of P_T^* , firms again maximize profits by producing where short run marginal cost ($SRMC^2$) is equal to the price. Each firm now produces only q^2 rides. Profits decrease from Profits^1 to Profits^2 . Profits are again the difference between price, P_T^* , and the short run average total cost of producing q^2 , $SRATC(q^2)$, multiplied by q^2 . The decrease in profits decreases the demand for taxi medallions, as it is now less profitable to operate a taxi. Demand for medallions decreases to D_M^2 , which reduces the equilibrium price of a medallion to P_M^2 (which is equal to Profits^2 in the first panel of figure 5). The size of the decrease in medallion price is dependent on the magnitude of the decrease in profits. If profits are reduced to zero, the equilibrium price of a medallion will be zero, as operating a taxi or owning a medallion is now no more profitable than the next best alternative. If the demand for

taxi falls so much that profits are negative, firms will exit the market, short run supply will decrease, and entry regulations will no longer be binding.

Mathematical Model

I now mathematize the model by constructing supply and demand functions in both the market for taxi rides and the market for medallions. I am then able to derive comparative statics predictions for the parameters of the model. As will I will demonstrate, the comparative statics predictions are consistent with predictions from the graphical models.

Competitive Free Market

In a competitive market free of regulation consisting of n identical price taking firms, each firm faces the same short run profit equation. The following is the i^{th} firm's short run profit equation:

$$\pi_i = p_T * q_i - c(q_i, \alpha) - F$$

where π_i represents profits. p_T is the price of a taxi ride. q_i is the quantity of rides produced. $c(q_i, \alpha)$ is the variable cost function where α represents a vector of supply shifters such as changes in input prices—e.g., gasoline prices. F represents fixed costs for each firm. Each firm maximizes profits by producing the quantity of rides at which marginal cost— $c'(q_i, \alpha)$ —equals the market price— p_T . The quantity supplied by each firm is now a function of the market price and supply shifters, yielding the following firm supply function:

$$s_i = q_i(p_T, \alpha)$$

The short run market supply of taxi rides is equal to the horizontal summation of all firms' supply function:

$$Q_S^T = S^T(p_T, \alpha) = \sum_{i=1}^n q_i(p_T, \alpha)$$

where the market supply is a function of the price of taxi rides and supply shifters.

The market demand for taxis is a function of the price of taxi rides and demand shifters, which yields the following market demand function:

$$Q_D^T = D^T(p_T, \beta)$$

p_T is again the price of taxi rides. β represents a set of demand shifters such as income, the price of substitute services, and the price of complementary services. In this free market model, the short run equilibrium price, quantity, and the number of firms in the industry are determined by setting market demand (Q_D^T) equal to market supply (Q_S^T).

Market for Medallions

The current market for taxi services is regulated by the medallion system in each of the four cities in this study. The supply of medallions is set by each city's regulatory agency. Thus the supply function for medallions is:

$$Q_S^M = \bar{M}$$

where $\bar{M}$ is the number of medallions issued in the city. As previously discussed, $\bar{M}$ changes when the regulatory agency increases the number of medallions via auctions, lotteries or a queuing system. Because the number of medallions directly impacts the number of firms in the industry, the market supply of taxi rides is now a function of $\bar{M}$ along with the price of taxi rides, p_T , and supply shifters, α :

$$Q_S^T = S^T(p_T, \alpha, \bar{M}) = \sum_{i=1}^{\bar{M}} q_i(p_T, \alpha)$$

The demand for medallions is created by the willingness to pay for the rights to operate a taxi. The willingness to pay for a medallion depends on the profits associated with operating a taxi. If profits are zero, the willingness to pay for a medallion is zero. As profits increase, the willingness to pay for a medallion rises. Thus, the demand for medallions is a function of the price of a medallion, p_m , and the price of taxi rides, p_T , because the price of taxi rides directly impacts profits. The following equation represents the demand for taxi medallions:

$$Q_D^M = D^M(p_m, p_T)$$

Application

Incorporating medallion regulation into the competitive market model above yields the following four equations:

$$\begin{aligned} Q_S^T &= S^T(p_T, \alpha, \bar{M}) & Q_D^T &= D^T(p_T, \beta) \\ Q_S^M &= \bar{M} & Q_D^M &= D^M(p_m, p_T) \end{aligned}$$

where Q_S^T is the supply of taxi services, Q_D^T is the demand for taxi services, Q_S^M is the supply of taxi medallions, and Q_D^M is the demand for taxi medallions. The market equilibrium for taxi services is achieved when $Q_S^T = Q_D^T$:

$$S^T(p_T, \alpha, \bar{M}) = D^T(p_T, \beta)$$

Given a set of parameters α, β , and $\bar{M}$, there exists a market price, p_T , such that the market is in equilibrium. More broadly, in equilibrium, the market price of taxi services is a function of the parameters of taxi service supply and demand:

$$p_T = p_T^*(\alpha, \beta, \bar{M}) \quad (5)$$

Similarly, medallion market equilibrium occurs when $Q_S^M = Q_D^M$:

$$\bar{M} = D^M(p_m, p_t)$$

In equilibrium, the price of medallions, p_m , is a function of the parameters of medallion supply and demand and those of taxi service supply and demand:

$$p_m = p_m^*(\alpha, \beta, \bar{M}) \quad (6)$$

Substituting the market clearing prices into each set of market equations creates identities as the new price functions clear markets for any given set of parameters. Thus:

$$S^T(p_T^*(\alpha, \beta, \bar{M}), \alpha, \bar{M}) \equiv D^T(p_T^*(\alpha, \beta, \bar{M}), \beta) \quad (7)$$

$$\bar{M} \equiv D^M(p_m^*(\alpha, \beta, \bar{M}), p_T^*(\alpha, \beta, \bar{M})) \quad (8)$$

The identities allow for the derivation of comparative statics results. Comparative statics results for the three parameters of the model, β_1 , α_1 , and $\bar{M}$, will be explored here.

Differentiating the identities with respect to β_1 allows me to solve for the comparative statics results associated with a change in β_1 —a demand shifter:

$$\begin{aligned} \frac{\partial S^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \beta_1} &= \frac{\partial D^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \beta_1} + \frac{\partial D^T(\cdot)}{\partial \beta_1} \\ 0 &= \frac{\partial D^M(\cdot)}{\partial p_m} \cdot \frac{\partial p_m^*}{\partial \beta_1} + \frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \beta_1} \end{aligned}$$

Rearranging in matrix notation:

$$\begin{bmatrix} \left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{bmatrix} \begin{bmatrix} \frac{\partial p_T^*}{\partial \beta_1} \\ \frac{\partial p_m^*}{\partial \beta_1} \end{bmatrix} = \begin{bmatrix} \frac{\partial D^T(\cdot)}{\partial \beta_1} \\ 0 \end{bmatrix}$$

Using Cramer's Rule to solve for $\frac{\partial p_T^*}{\partial \beta_1}$:

$$\frac{\partial p_T^*}{\partial \beta_1} = \frac{\begin{vmatrix} \frac{\partial D^T(\cdot)}{\partial \beta_1} & 0 \\ 0 & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{\frac{\partial D^T(\cdot)}{\partial \beta_1} \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}{\left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

Assuming that the demand for taxi services and the demand for medallions are downward sloping and the supply of taxi services is upward sloping, $\frac{\partial p_T^*}{\partial \beta_1} > 0$. According to this finding, a positive shift in demand for taxi services leads to an increase in the price of taxi services. Conversely, a decrease in the demand for taxi services (i.e., a decrease in demand) results in a decrease in the price of taxi services. This finding is intuitive consistent with the graphical theoretical framework.

Again using Cramer's Rule, I solve for $\frac{\partial p_m^*}{\partial \beta_1}$:

$$\frac{\partial p_m^*}{\partial \beta_1} = \frac{\begin{vmatrix} \left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) & \frac{\partial D^T(\cdot)}{\partial \beta_1} \\ \frac{\partial D^M(\cdot)}{\partial p_T} & 0 \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{-\frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial D^T(\cdot)}{\partial \beta_1}}{\left(\frac{\partial S^T(\cdot)}{\partial p_T} - \frac{\partial D^T(\cdot)}{\partial p_T} \right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

Assuming again that the demand for taxi services and medallion values are again assumed to be downward sloping, taxi service supply to be upward sloping, and p_T changes as a result of a change in demand, $\frac{\partial p_m^*}{\partial \beta_1} > 0$.²⁹ This implies that if demand for taxi services increases, the price of taxi medallions increases. Alternatively, if demand for taxi services decreases—as it likely did when Uber entered and expanded in the transportation industry—the price of taxi medallions decreases. $\frac{\partial p_m^*}{\partial \beta_1} > 0$ is consistent with the graphical model predictions.

Differentiating the identities in equations (7) and (8) with respect to α_1 allows for the derivation of the comparative statics results associated with a change α_1 , a supply shifter:

$$\begin{aligned} \frac{\partial S^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \alpha_1} + \frac{\partial S^T(\cdot)}{\partial \alpha_1} &= \frac{\partial D^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \alpha_1} \\ 0 &= \frac{\partial D^M(\cdot)}{\partial p_m} \cdot \frac{\partial p_m^*}{\partial \alpha_1} + \frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \alpha_1} \end{aligned}$$

Rearranging in matrix notation:

$$\begin{bmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{bmatrix} \begin{bmatrix} \frac{\partial p_T^*}{\partial \alpha_1} \\ \frac{\partial p_m^*}{\partial \alpha_1} \end{bmatrix} = \begin{bmatrix} \frac{\partial S^T(\cdot)}{\partial \alpha_1} \\ 0 \end{bmatrix}$$

²⁹ When p_T changes as a result of changes in demand, $\frac{\partial D^M(\cdot)}{\partial p_T} > 0$, but when p_T changes as a result of changes in supply, $\frac{\partial D^M(\cdot)}{\partial p_T} < 0$. Because I am differentiating with respect to a change in demand, $\frac{\partial D^M(\cdot)}{\partial p_T} > 0$ here.

Using Cramer's Rule to solve for $\frac{\partial p_T^*}{\partial \alpha_1}$:

$$\frac{\partial p_T^*}{\partial \alpha_1} = \frac{\begin{vmatrix} \frac{\partial S^T(\cdot)}{\partial \alpha_1} & 0 \\ 0 & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{\frac{\partial S^T(\cdot)}{\partial \alpha_1} \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}{\left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

Assuming that the demand for taxi services and the demand for medallions are downward sloping and the supply of taxi services is upward sloping, $\frac{\partial p_T^*}{\partial \alpha_1} < 0$. According to this finding, a positive, or outward, shift in the supply of taxi services—caused, for example, by a decrease in input costs such as gasoline—leads to a decrease in the price of taxi services. Alternatively, a negative/inward shift in supply results in an increase in the price of taxi services.

Using Cramer's Rule once again, I solve for $\frac{\partial p_m^*}{\partial \alpha_1}$:

$$\frac{\partial p_m^*}{\partial \alpha_1} = \frac{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & \frac{\partial S^T(\cdot)}{\partial \alpha_1} \\ \frac{\partial D^M(\cdot)}{\partial p_T} & 0 \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{-\frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial S^T(\cdot)}{\partial \alpha_1}}{\left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

Again under the assumptions that the demand for taxi services and the demand for medallions are downward sloping, the supply of taxi services is upward sloping, and the

change in p_T is due to a change in supply, $\frac{\partial p_m^*}{\partial \alpha_1} > 0$.³⁰ This comparative static result suggests that a positive/outward shift in the supply of taxi services increases the price of taxi medallions.

Differentiating the identities (7) and (8) with respect to $\bar{M}$ allows me to solve for the comparative statics results associated with a change in the number of medallions issued:

$$\begin{aligned} \frac{\partial S^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \bar{M}} + \frac{\partial S^T(\cdot)}{\partial \bar{M}} &= \frac{\partial D^T(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \bar{M}} \\ 1 &= \frac{\partial D^M(\cdot)}{\partial p_m} \cdot \frac{\partial p_m^*}{\partial \bar{M}} + \frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial p_T^*}{\partial \bar{M}} \end{aligned}$$

Rearranging in matrix notation:

$$\begin{bmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{bmatrix} \begin{bmatrix} \frac{\partial p_T^*}{\partial \bar{M}} \\ \frac{\partial p_m^*}{\partial \bar{M}} \end{bmatrix} = \begin{bmatrix} \frac{\partial S^T(\cdot)}{\partial \bar{M}} \\ 1 \end{bmatrix}$$

Using Cramer's Rule to solve for $\frac{\partial p_T^*}{\partial \bar{M}}$:

$$\frac{\partial p_T^*}{\partial \bar{M}} = \frac{\begin{vmatrix} \frac{\partial S^T(\cdot)}{\partial \bar{M}} & 0 \\ 1 & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{\frac{\partial S^T(\cdot)}{\partial \bar{M}} \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}{\left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T} \right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

³⁰ When p_T changes as a result of changes in demand, $\frac{\partial D^M(\cdot)}{\partial p_T} > 0$, but when p_T changes as a result of changes in supply, $\frac{\partial D^M(\cdot)}{\partial p_T} < 0$. Because I am differentiating with respect to a change in supply, $\frac{\partial D^M(\cdot)}{\partial p_T} > 0$ here. Recall the Envelope Theorem that states an increase in price leads to an increase in profits and thus a change in price resulting from a decrease in supply (e.g., an increase in input prices) increases the demand for medallions

If demand for both taxi services and medallions are once again assumed to be downward sloping and supply of taxi services is assumed to be upward sloping, $\frac{\partial p_T^*}{\partial \bar{M}} < 0$. This result implies that a change in the number of medallions issued has an effect in the opposite direction on the price of taxi services (i.e., increasing the number of taxis in operation decreases the price of taxi services).

Using Cramer's rule to solve for $\frac{\partial p_m^*}{\partial \bar{M}}$:

$$\frac{\partial p_m^*}{\partial \bar{M}} = \frac{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T}\right) & \frac{\partial S^T(\cdot)}{\partial \bar{M}} \\ \frac{\partial D^M(\cdot)}{\partial p_T} & 1 \end{vmatrix}}{\begin{vmatrix} \left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T}\right) & 0 \\ \frac{\partial D^M(\cdot)}{\partial p_T} & \frac{\partial D^M(\cdot)}{\partial p_m} \end{vmatrix}} = \frac{\left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T}\right) - \left(\frac{\partial D^M(\cdot)}{\partial p_T} \cdot \frac{\partial S^T(\cdot)}{\partial \bar{M}}\right)}{\left(\frac{\partial D^T(\cdot)}{\partial p_T} - \frac{\partial S^T(\cdot)}{\partial p_T}\right) \cdot \frac{\partial D^M(\cdot)}{\partial p_m}}$$

Assuming downward sloping demand for taxi services and taxi medallions, that supply of taxi services is upward sloping, and that an increase in $\bar{M}$ increases supply, $\frac{\partial p_m^*}{\partial \bar{M}} < 0$.

Predictions from the two graphical models and the mathematical models are consistent. While the mathematical model does not incorporate fixed taxi fare rates, predictions would likely be unchanged if it were included. Predictions from the graphical models are unchanged with the addition of the fixed fare rates and because of this it is probable that comparative static results will not change with the addition of fixed fare rates to the model. All models suggest that a decrease in the demand for taxi services—from, for example, the introduction and expansion of Uber—decreases medallion values.

DATA

Data on medallion transfer prices and auction data proved challenging to collect. The data—historical data specifically—are generally not readily available on the regulatory agency’s webpages. Countless phone calls were made and emails exchanged to collect these data and correctly interpret them. Numerous “Freedom of Information Act” requests were filed requesting the data from the regulatory agencies of each city. Once the data were obtained, many conversations with employees of the regulatory agencies followed to ensure I was correctly interpreting of the data.

Taxi Medallion Transfer Price Data

Data on taxi medallion transfers were obtained from the taxi regulatory agency of each respective city. These data consist of the date the transfer occurred, the dollar amount of the transfer, and in some cases, the type of medallion and medallion identification number. Medallion transfer prices below \$10,000 were dropped from the sample. These observations were substantially lower than the monthly average transfer prices of their respective city. Additionally, notes in the transfer price data suggest that many of these low priced transfers were transfers between family members or members within corporations and thus are not representative of the true market value of a medallion. The TLC supplied the medallion transfer data for New York City. The New York City data span the period of 1947-2015 and can be thought of in three different segments. The earlier data—1947, 1950, 1952, and 1960-1991—provide the annual average transfer price for both individual and corporate taxi medallions. The middle

section of the data—1992-2005—consists of the monthly average of both types of taxi medallions. The most recent section of the data—2006-2015—contains transaction level data on taxi medallion transfers and details of the transfer such as whether it was an asset or stock transfer, whether the medallion transferred was an individual or corporate medallion, and whether the medallion transferred was designated a wheelchair accessible or an alternative fuel medallion.³¹

Taxi medallion transfer price data for Chicago were obtained from the City of Chicago and the Chicago Dispatcher.³² The data are at the individual transaction level and span the period 2007-2015. As discussed previously, Chicago does not issue specific medallions to be used for taxis that are wheelchair accessible or use alternative fuel. The Chicago transfer price data do not distinguish between independent or corporate medallion transfers although Chicago does have both types of medallions. As a result, transfer price data from Chicago contain only the date of the transfer and the amount.³³

The Boston data were gathered from two sources, Carriage News—a now defunct private trade newspaper—and the Hackney Carriage Unit of the Boston Police Department.³⁴ The data are again at the individual transaction level and cover the time period of January 2009 to April 2015.³⁵ Recall, the City of Boston does not designate

³¹ Wheelchair accessible medallions must be used in vehicles that can transport wheelchair bound passengers and alternative fuel medallions must be used on vehicles that use alternative fuel.

³² The Chicago Dispatcher publishes medallion transfer price data obtained from the City of Chicago. The Chicago Dispatcher's archives go back further than those of Chicago, making it advantageous to use data from them as well as the City of Chicago.

³³ The medallion number of the medallion transferred is also recorded but that information is not used in my analysis. The medallion numbers do not have any characteristics that allow me to determine if a medallion is an independent or corporate (standard) medallion.

³⁴ The data from December 2014 – April 2015 were obtained from a report by HVM Capital that listed the transfers and cited the Hackney Carriage Unit as a source. After numerous unanswered requests to the Hackney Carriage Unit for the original data, the data from the HVM Capital Report were used.

³⁵ I am in the process of requesting more recent data from the Hackney Carriage Unit of the Boston Police Department.

specific medallions that must be used in wheelchair accessible taxis, but instead mandates that ten percent of taxis must be wheelchair accessible (Fichtenbaum, 2013). Because of this, there are no wheelchair accessible medallions in the Boston data. Data on medallion transfers in Philadelphia were collected from the Philadelphia Parking Authority (PPA), which regulates taxis across the city. These individual transfer data span from January 2006 to December 2015. The data consist of the transfer date, medallion number(s), and price. The PPA supplied me with a list of the medallion numbers that refer to wheelchair accessible medallions. By matching the medallion number listed on the transfer with the list of medallion numbers that are required to be used for taxis offering wheelchair accessible services, I was able to distinguish which transfers were of wheelchair accessible medallions.

Auction Data

New York City taxi medallion auction data were also obtained from the TLC and have similar information as the transfer price data—the date of the auction, type of medallion(s) auctioned, and the amount of the winning bid(s). The data cover all auctions of medallions from 2004 to the most recent auction in 2014.³⁶ A few prices from the 1996 and 1997 auctions were mentioned in news articles, but the TLC no longer has data on all winning bids from these auctions.

Data from Chicago taxi medallion auctions in 2010 and 2013 were provided by the City of Chicago and contain the date, winning bid amount, and the type of medallion

³⁶ Most auction data include both winning and non-winning bids. For some of the auctions, non-winning bids were requested. The TLC responded and said they would collect and submit the data for specified monetary amount. Because the benefit of acquiring these bids was less than the cost, the non-winning bids were not collected.

auctioned (individual vs. corporate). As discussed above, the 2013 auction of 50 medallions was never finalized. Due to this, the 2013 auction bids will not be used in the analysis. Philadelphia auction data were retrieved from the PPA and consist of the only auction that took place during the span of January 2006 to December 2015. The auction was conducted from May 2015 – July 2015. The data again include the date of the auction, the winning bid amount, and the type of medallion auctioned.³⁷ During the period of time for which I have transfer price data, January 2009 to April 2015, there were no auctions in Boston.

Active Uber Drivers Over Time

The number of active Uber drivers are from figure 3 in Hall and Krueger's (2016) paper. Figure 3 shows the number of active Uber drivers in major U.S. metropolitan areas over time. The original data were requested from Hall but our request was politely declined. As a result, the estimates were created by replicating the graph in Hall and Krueger (2016) using WebPlotDigitizer. WebPlotDigitizer is a software application that extracts data from plots. The process involves magnifying the figure, calibrating the axes, mapping out data points exactly mirroring those in the figure, and then extracting the data as x-y coordinates. To ensure accuracy, two different people completed this process two separate times.³⁸ Once the two replications were complete, the estimations were compared both statistically and graphically and were notably similar to one another.³⁹

³⁷ All medallions sold in the Philadelphia auction were wheelchair accessible medallions. These data have yet to be merged in and used in the results but they will be in the near future.

³⁸ Thank you to Kadeem Noray for assisting me in this process.

³⁹ Correlations and plots of the data were constructed. All correlations were above 0.9 and plots were nearly identical.

The data are available at the monthly level and begin in June 2012 and end in December 2015. One shortcoming of these data is that they begin after Uber entered each of the four cities. But, because the number of drivers was so low in the initial introduction of Uber to the cities, assigning zero values to the number of Uber drivers until the actual data are available does not compromise the overall trend of the number of drivers in each city over time.

Control Variables

Unemployment data are seasonally unadjusted monthly unemployment rates from the U.S. Bureau of Labor Statistics (U.S. Bureau of Labor Statistics 2016). Population estimates are from the U.S. Census Bureau and are annual estimates by city (U.S. Census Bureau 2016). Gasoline price data are monthly average prices per gallon by city—with the exception of Philadelphia—and are from the U.S. Energy Information Administration (EIA) (U.S. Energy Information Administration 2016).⁴⁰ The monthly real interest rate data are from Yi and Zhang’s paper, *Real Interest Rates over the Long Run* (2016) and are constructed by subtracting the CPI inflation rate from the Federal Funds rate. The number of active medallions per city is estimated using data provided from each city’s taxi regulatory agency.

⁴⁰ Averages are calculated from all grades and all formulations of retail gasoline. Gasoline price data over time were not available for Philadelphia exclusively. In its place, I used gasoline price data for PADD 1B—a region defined by the EIA that covers New York, Pennsylvania, New Jersey, Delaware, and Maryland. Because gasoline prices are not highly variable across a small geographic space, using the PADD 1B data does not pose a problem.

Summary Statistics

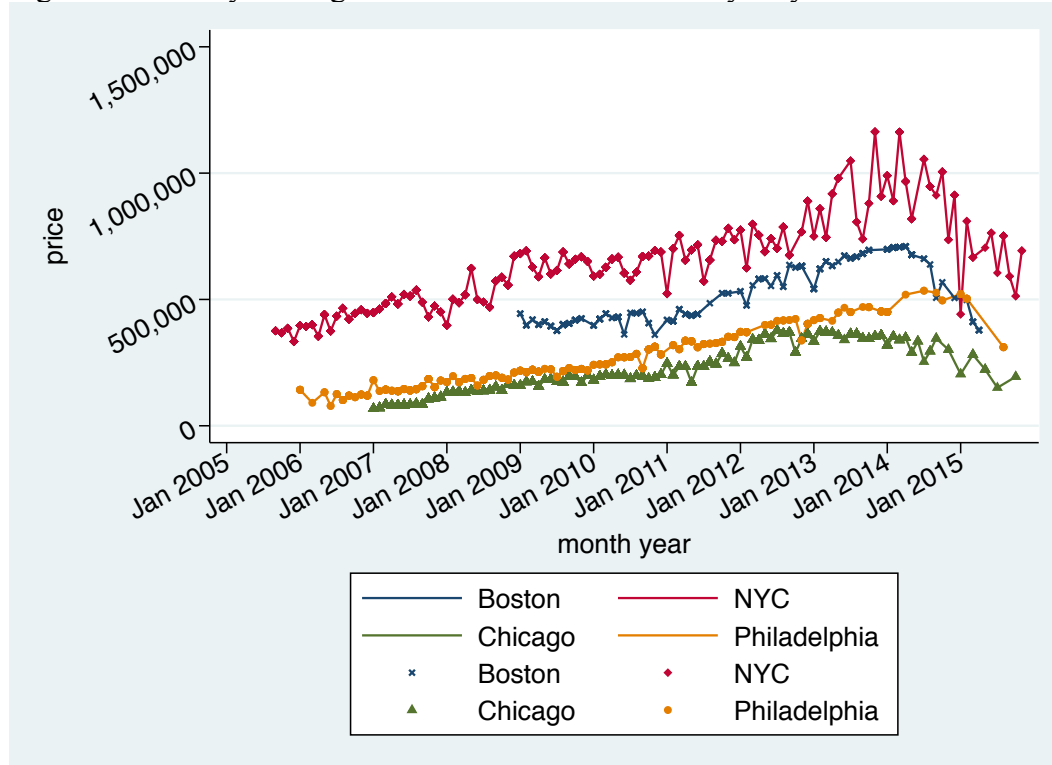
Table 2 provides summary statistics for the variables used in my empirical analysis. The mean transfer price of the full sample is roughly \$380,000. New York City's mean transfer price is the highest at over \$590,000 while Chicago exhibits the lowest average price at about \$215,000 per medallion. Based upon an initial inspection of the data, these differences are potentially driven by city characteristics like population, the demand for taxi services, and the time period of the data in Boston specifically. The number of active taxis also varies across cities, and in a given city across time. New York City again leads with an average of 13,081 active taxi medallions, followed by Chicago, Boston, and finally Philadelphia. Similarly, the number of observations for each city—which is the number of medallion sales per city—varies dramatically across the four cities. This number includes transfers between individuals and/or corporations and medallions sold by auction from a city. It appears that medallions are transferred or sold most frequently in Chicago. The reason for this is not apparent. Differing transaction costs, transfer fees, or access to market information could be driving these differences, but is unclear without further investigation. All variables were plotted over time and inspected for outliers. In addition to visually inspecting plots of the data, minimum and maximum values were reviewed to ensure the integrity of the data.

Table 2: Summary Statistics: Means, standard deviations, minimums, and maximums for full sample and by city

Variable		All Cities	NYC	Chicago	Philadelphia	Boston
Dependent variable:						
Medallion transfer price	<i>Mean</i>	\$380,126.60	\$590,151.90	\$214,847.30	\$256,040.50	\$525,041.40
	<i>Standard deviation</i>	(255911.7)	(254241.60)	(105124.20)	(111918)	(124418.6)
	<i>Minimum</i>	\$10,907.14	\$17,398.42	\$12,405	\$10,907.14	\$302,506.90
	<i>Maximum</i>	\$1,948,424	\$1,948,424	\$408,933	\$552,314	\$716,270
Independent variable:						
Number of active Uber drivers	<i>Mean</i>	664	1037.39	399.66	145.88	1,252.07
	<i>Standard deviation</i>	(2291.18)	(3003.89)	(1591.55)	(786.37)	(2647.34)
	<i>Minimum</i>	0	0	0	0	0
	<i>Maximum</i>	31,787	28,326	31,787	7,921	13,056
City level controls:						
Gasoline price per gallon	<i>Mean</i>	\$3.47	\$3.28	\$3.65	\$3.34	\$3.38
	<i>Standard deviation</i>	(0.64)	(0.61)	(0.63)	(0.56)	(0.55)
	<i>Minimum</i>	\$1.94	\$2.01	\$1.94	\$2.04	\$1.95
	<i>Maximum</i>	\$4.74	\$4.68	\$4.74	\$4.62	\$4.27
Unemployment rate	<i>Mean</i>	8.20	7.11	9.16	8.70	6.60
	<i>Standard deviation</i>	(2.26)	(1.85)	(2.21)	(1.95)	(1.09)
	<i>Minimum</i>	4.20	4.40	5.00	5.40	4.20
	<i>Maximum</i>	12.60	10.50	12.60	12.00	8.40
Population	<i>Mean</i>	4,702,297	8,159,690	2,706,009	1,519,932	635,862
	<i>Standard deviation</i>	(2863146)	(175113.60)	(9148.25)	(24148.17)	(18559.05)
	<i>Minimum</i>	612,669	7,993,906	2,697,006	1,488,710	612,669
	<i>Maximum</i>	8,550,405	8,550,405	2,723,436	1,567,442	667,137
Number of medallions	<i>Mean</i>	9,862	13,081.29	6,851.25	1,599.24	1,825
	<i>Standard deviation</i>	(3538.54)	(81.88)	(46.87)	(2.68)	(0.00)
	<i>Minimum</i>	1,825	13,049	6,792	1,599	1,825
	<i>Maximum</i>	13,333	13,333	6,904	1,629	1,825
Real Interest Rate	<i>Mean</i>	-0.706				
	<i>Standard deviation</i>	(1.84)				
	<i>Minimum</i>	-3.74				
	<i>Maximum</i>	3.84				
Sample Period		Sept '05 - Dec '15	Sept '05 - Dec '15	Jan '07 - Dec '15	Jan '06 - Dec '15	Jan '09 - Apr '15
Number of Observations:		7,058	2,820	3,349	623	266

Notes: All prices in 2016 dollars. Unemployment rates are unadjusted. **Sources:** Hall and Kruger 2016, U.S. Census Bureau 2016, U.S. Energy Information Administration 2016, U.S. Bureau of Labor Statistics 2016, and Yi and Zhang 2016.

Figure 6: Monthly Average Medallion Transfer Prices by City



Note: Average transfer prices exclude auction sale prices.

Figure 6 plots the monthly average medallion transfer price by city over time. All prices are deflated to 2016 dollar values. As anticipated by the summary statistics, with the exception of one seemingly anomalous month, NYC has the highest monthly averages for nearly the entire time period. Overall, medallion values appear to be upward trending until about 2014 and then begin to decrease. While this decrease does not perfectly match the time of Uber's entrance to each city, it is possible that Uber's effect on taxi medallion values was delayed following its entrance and only took effect once the rideshare company grew in popularity. The overall trend, however, should be accounted for in estimation either by the inclusion of control variables or, if the model is not perfectly identified, by implementing a time trend.

Figure 7: Monthly Average Gasoline Prices by City

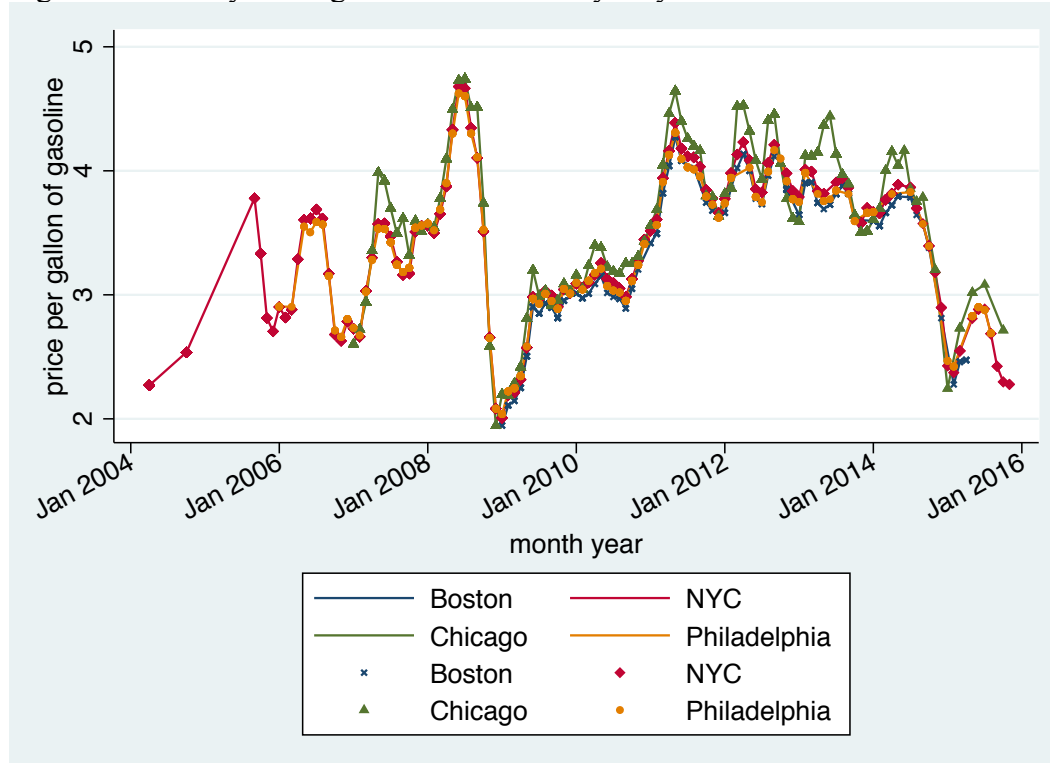
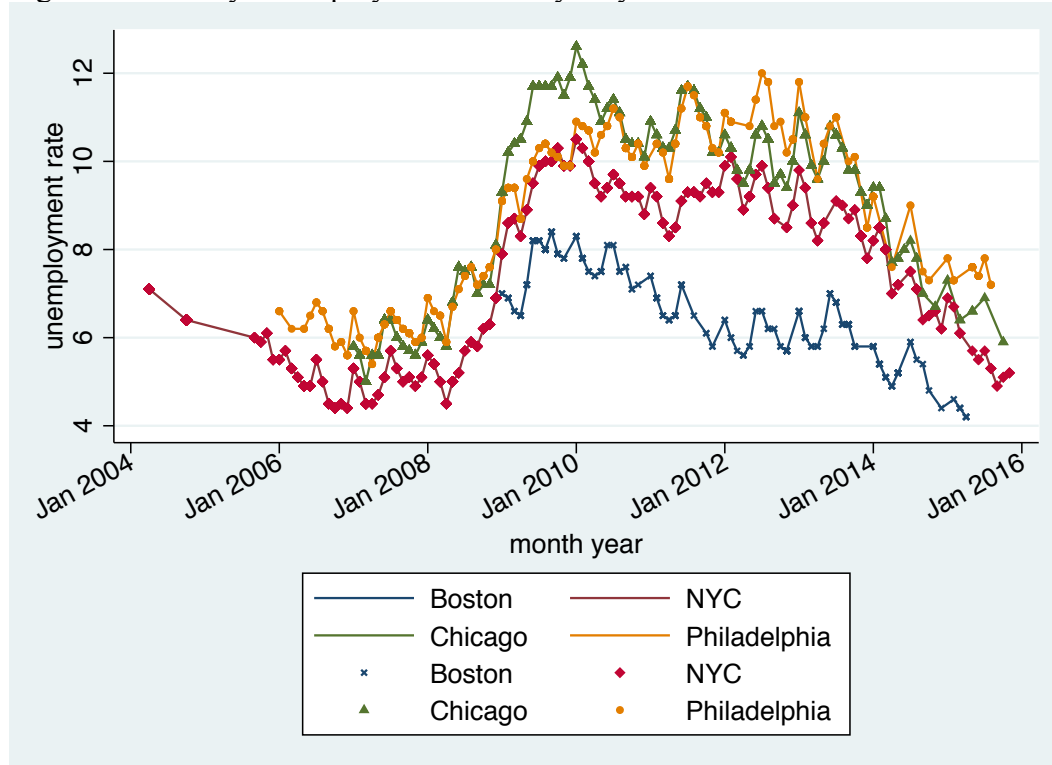


Figure 7 plots the monthly average gasoline prices by city over the time span of the sample. Gasoline prices across cities appear highly correlated and similar in magnitude. There is some evidence of seasonality in gasoline prices with prices peaking in the summer months and decreasing in winter months (i.e., December and January). The large drop in gasoline prices that occurred from August 2008 – January 2009 has been cited as being driven by reduced demand in response to record high prices and uncertain future expectations (Officer 2008). The similarity in both the trend of gasoline prices and the magnitude further suggests that using the PADD 1B gasoline data for Philadelphia will not comprise results.⁴¹

⁴¹ PADD 1B gasoline price data is the average gasoline price of New York, Pennsylvania, New Jersey, Delaware, and Maryland.

Figure 8: Monthly Unemployment Rates by City



As shown in figure 8, unemployment rates also have similar trends over time across the sample cities. NYC Chicago and Philadelphia unemployment rates are of similar magnitude while Boston has relatively lower unemployment. Including the unemployment rate in the model helps control for economic conditions, because unemployment is reflective to changes in the economy. From roughly January 2008 to January 2010, there is a large increase in unemployment, which corresponds to the Great Recession. Post January 2010, unemployment rates appear to decrease, on average, for the remaining time span of the sample. This decrease in unemployment suggests that the economy was recovering from the Great Recession during this period. Because Uber enters the sample cities during a time expansion and medallion values are affected by the state of the economy, controlling for the state of the economy is vital in estimating

unbiased results and including the unemployment rate controls for these changes in the economy.

Figure 9: NYC Population

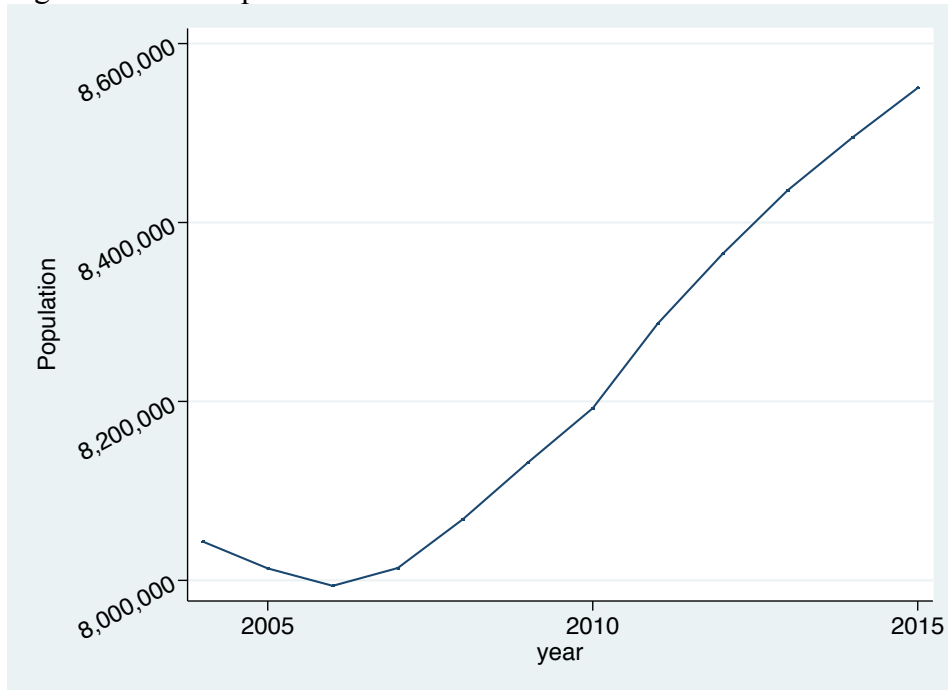


Figure 10: Chicago Population



Figure 11: Boston Population

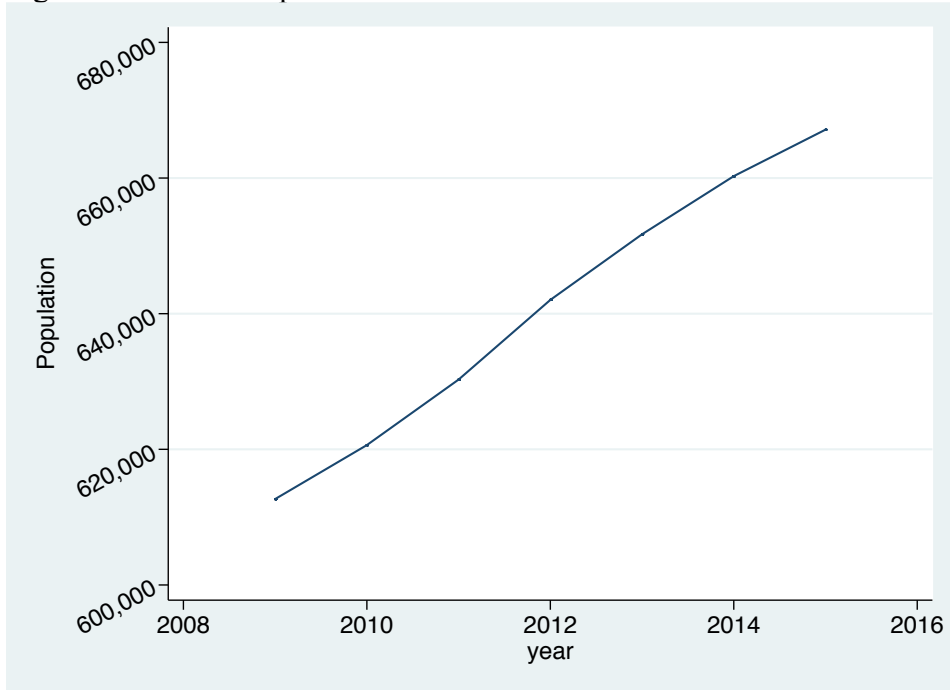
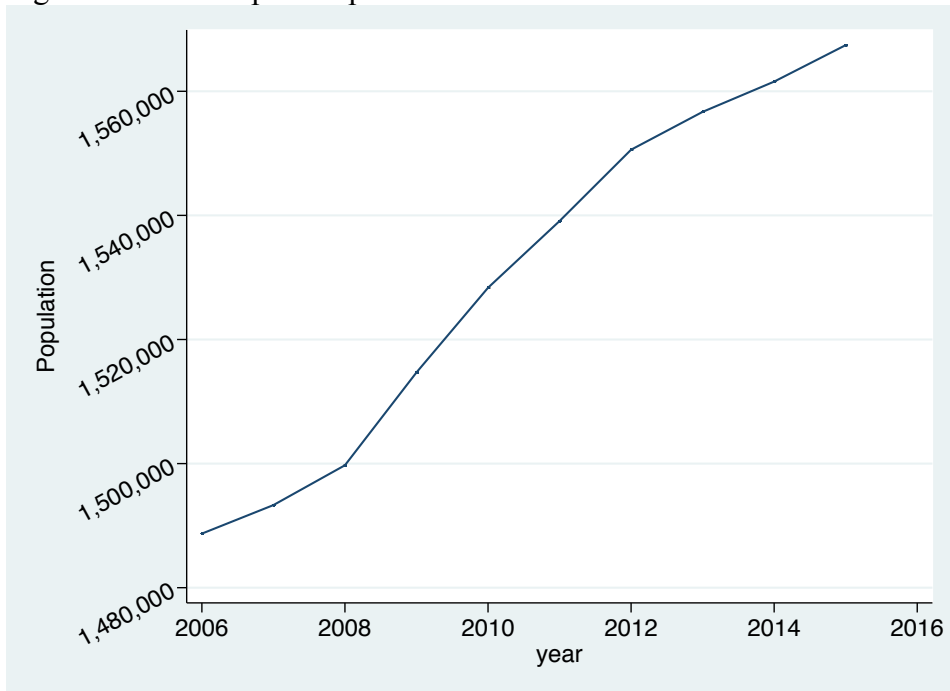


Figure 12: Philadelphia Population



Figures 9-12 show population across sample periods for each city in the study. Overall, population is increasing over time. Boston has the lowest population with a mean of about 635,000 people. NYC has the highest population with a sample mean of over 8.1 million people. Chicago and Philadelphia fall in the middle of the sample with mean populations of 2.7 and 1.5 million people. Including population in the model helps control for changes in the demand for taxis driven by changes in the number of consumers in each city.

Figure 13: Monthly Real Interest Rate

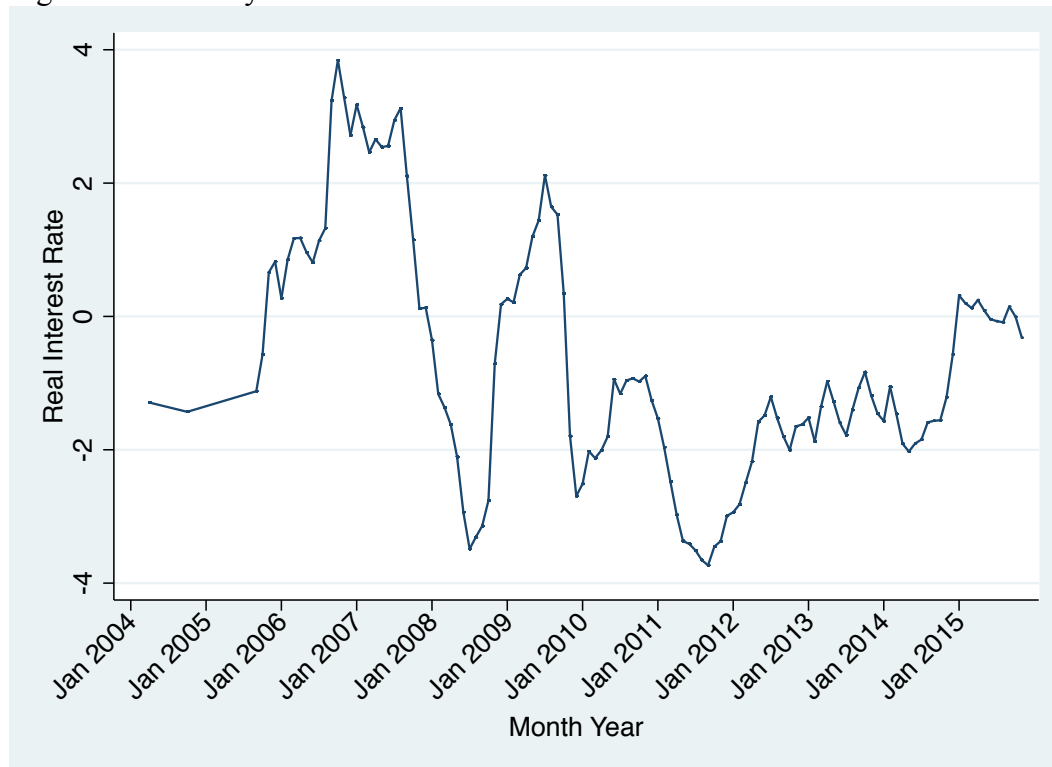


Figure 13 plots the real interest rate measure over time. The real interest rate helps control for changes in medallion values due to change in the value of discounted future profits associated with a change in the real interest rate. The real interest rate increases prior to the Great Recession. From mid 2007 to mid 2012, the real interest rate is quite

variable—decreasing sharply and then recovering roughly three times. Toward the end of the sample period, around the beginning of 2015, real interest rates increase but are still considerably lower than pre recession levels.

ESTIIMATIONS BY CITY

Empirical Model

The relationship of interest measured here is the effect of the entrance of Uber on the value of taxi medallions in a given city. To estimated this effect, I estimate the following ordinary least squares (OLS) regression for each of the four cities in my study:

$$\begin{aligned}
 (1) \quad Med_Trans_Price_{it} &= \beta_0 + \beta_1 Num_Drivers_t + \beta_2 Num_Drivers_t^2 + \beta_3 WAC_{it} \\
 &+ \beta_4 AltFuel_{it} + \beta_5 Independent_{it} + \beta_6 Auction_{it} + \mathbf{X}_t \boldsymbol{\lambda} + \phi * t + \theta \\
 &* t^2 + \varepsilon_{it}
 \end{aligned}$$

This equation is estimated separately for each city in my sample. Results are listed by city in table 2. For a given city, the dependent variable, $Med_Trans_Price_{it}$ is the price of transfer i at time t in 2016 dollars. The primary independent variable of interest is $Num_Drivers_t$, which is the number of Uber drivers at time t . In my analysis, I also add a quadratic term to the $Num_Drivers_t$ variable. Adding a quadratic term allows the effect of Uber on medallion values to change as the number of Uber drivers change. In the absence of the quadratic term, I expect β_1 to be negative as my model predicts the entry and expansion of Uber to decrease the demand for taxis and thus decrease the value of taxis medallions.

With the quadratic term added to the $Num_Drivers_t$ variable, I can image scenarios in which β_1 is negative and scenarios when it is positive. In interpreting β_1 and β_2 , the equation is derived with respect to $Num_Drivers_t$. β_2 explains how the effect of Uber changes as the number of Uber drivers change. β_2 will be be negative if the effect

of an additional Uber driver increases (i.e., becomes more negative) as the number of Uber drivers increase and β_2 will be positive if the effect decreases as drivers increase. The sign of β_1 is unclear. If the negative effect of Uber on medallion values appears as soon as Uber enters the market—i.e., as soon as there is at least one driver—I would expect β_1 to be negative and either increasing or decreasing in magnitude with increases in the number of drivers. Alternatively, let's assume the effect of Uber is a bit delayed, which might be the case if the demand for taxis is high enough that a decrease in the demand for taxis is not initially noticed by taxi drivers. In this scenario β_1 might be positive and the negative effect of Uber on taxi medallion values becomes apparent only after the number of drivers has passed a certain threshold.

WAC_{it} is an indicator variable equaling one if transfer i at time t is a transfer or sale of a wheelchair accessible medallion. β_3 will likely be negative as operating wheelchair accessible taxis has been cited as being more expensive. Wheelchair accessible vehicles are more costly than standard taxis, the vehicles are generally less fuel efficient, and insurance rates are—at times—higher for these vehicles (Fichtenbaum, 2013). $AltFuel_{it}$ is an indicator variable equaling one if transfer i at time t is the transfers of an alternative fuel medallion. β_4 is predicted to be negative as it restricts the options of vehicles that can be used as a taxicab. $Independent_{it}$ is an indicator variable equaling one if the transfer or sale is of an independent medallion, and equaling zero if the sale or transfer is of a corporate medallion. β_5 is predicted to be negative because there are fewer opportunities for growth with independent medallions than a corporate medallion, because independent medallions cannot be owned in quantities greater than two. In addition, it is possible that corporate medallion holders enjoy economies of scale in terms

of taxi storage costs or insurance rates, making corporate medallions worth more on average than independent medallions. $Auction_{it}$ is an indicator variable that equals one if the transfer—or sale—was via auction. One could make two different predictions about the value of β_5 . A medallion sold by auction could sell for a lower price if an auction immediately shifts out the supply of medallions and thus decreases the equilibrium price of a medallion. This, however, is unlikely as auctions of medallions are announced prior to the actual date of the auction and thus the supply of medallions increases—which causes medallion prices to decrease—at the time of the announcement rather than the time of the auction. Alternatively, a medallion sold via auction might be sold at a higher price as a result of the auction atmosphere itself. An increase in the number of buyers at an auction or sale results in higher bids than an auction or sale with a lower number of buyers. Because the auctions of medallions attracted many bidders, it is likely the winning auction bids are higher than medallion transfer prices as the amount of buyers at auctions are higher than in the negotiated sales of medallions.

X_t is a vector of city level controls at time t . The controls are the unemployment rate, population, monthly average gasoline prices, and real interest rates. An increase in the unemployment rate is predicted to have a negative effect on the value of a taxi medallion. When unemployment is high, consumers have less disposable income and might be more likely to choose lower priced substitutes to taxis such as public transportation, which decreases demand for taxis. Population is likely to have a positive relationship with medallion values. An increase in the number of consumers leads to an increase the demand for transportations and taxis specifically. Gasoline prices are predicted to have a negative relationship with medallion values. Gasoline is a direct input

to operating a taxi and an increase in gas prices will increase each firm's costs and decrease profits. The real interest rate is predicted to have a negative relationship with the value of a medallion. As the real interest rate increases, the discounted value of future profits associated with owning a medallion decrease. $\phi * t$ and $\theta * t^2$ represent linear and quadratic monthly time trend terms that are used to fit a quadratic time trend to the transfer prices overtime. This trend is included to account for the initially increasing then decreasing nature of the transfer prices over time that can be seen in figure 6. In a perfectly specified model, including a time trend would be unnecessary and doing so would yield a statistically insignificant coefficient estimate. While the control variables in this model explain some of the determinants of taxi medallion values, they do not perfectly explain all the determinants. Because data on the full costs of operating a taxi, revenues associated with owning a medallion, and both the price and availability of substitute goods are not readily available or easy to estimate, I incorporate the monthly trend in my model to account for these unattainable variables that affect medallion values. ε_{it} is the error term.

Results

In the next section, I present and discuss results using the above model—and several variants of it—in each of the four sample cities.⁴² New York City results are presented first, followed by Chicago, Boston, and Philadelphia. The same set of regression specifications are estimated are similar across cities and the results are generally consistent with predictions.

⁴² Note: Results represent one-tailed hypothesis tests conducted for all coefficients with sign predictions.

New York City

Table 3 presents New York City regression results. Each of the six columns in the table represents a different specification for estimation. Column one presents results from the simplest model. The model estimates a linear relationship between the number of Uber drivers and medallion values and does not control for any type of time trend in the value of taxi medallions over time. With this specification, the number of Uber drivers is estimated to have a negative—and statistically significant at the 1 percent level—impact on the value of taxi medallions in New York City. As predicted, wheelchair accessible and alternative medallions are estimated to be sold or transferred for a lower price. Independent medallions appear to be worth less than their corporate medallion counterparts. The coefficient estimate for the indicator variable for auction sales is estimated to be negative and statistically insignificant, which is inconsistent with the prediction that suggests an increase in the number of bidders leads to an increase in the price. Population has a positive estimated relationship with medallion values. This is consistent with the notion that an increase in population increases the demand for taxi services and thus increases the value of a medallion. The coefficient estimate for the unemployment rate is imprecisely estimated under this specification. The coefficient estimates for gasoline prices and the real interest rate are puzzling. Although the coefficient estimates are precisely estimated, they are of the opposite sign than predicted. This could be the result of gasoline prices and the real interest rate being closely correlated with omitted variables that have positive relationships with medallion values.

Table 3: Effect of Uber on taxi medallion values: NYC

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-14.45*** (2.74)	-22.79*** (2.69)	-33.22*** (3.20)	27.46*** (7.30)	12.88* (7.12)	-2.408 (8.58)
Number of Uber drivers ²				-0.00160*** (0.00026)	-0.00135*** (0.00025)	-0.00105*** (0.00027)
Wheelchair accessible medallion	-4,480 (16395)	-157,777*** (16271)	-143,371*** (16413)	-16,159 (16073)	-161,901*** (16653)	-151,063*** (16746)
Alternative fuel medallion	-54,455*** (15885)	-196,277*** (16049)	-182,168*** (16171)	-48,869*** (15913)	-186,267*** (16516)	-178,849*** (16434)
Independent medallion	-106,549*** (5762)	-83,492*** (5825)	-83,022*** (5756)	-106,566*** (5751)	-84,368*** (5817)	-83,845*** (5775)
Auction	-10,289 (11066)	201,173*** (15841)	166,727*** (16267)	-31,855*** (11800)	175,081*** (16859)	157,347*** (16711)
Population	1.357*** (0.070)	0.143* (0.102)	-1.024*** (0.197)	0.947*** (0.093)	-0.157* (0.115)	-0.891*** (0.199)
Unemployment rate	-753.2 (4099)	-23,311*** (4042)	-14,247*** (4073)	12,698*** (4407)	-11,122*** (4334)	-7,666** (4280)
Gasoline price per gallon	15,891* (9795)	-50,087*** (9135)	-49,016*** (9175)	28,072*** (9773)	-37,347*** (9052)	-39,510*** (9130)
Real interest rate	20,544*** (2938)	9,216*** (2572)	3291 (2746)	14,540*** (3118)	4,574* (2784)	1,559 (2820)
Linear monthly time trend		7,684*** (419.1)	-72,258*** (11800)		7,397*** (415.7)	-47,476*** (13021)
Quadratic monthly time trend			71.56*** (10.58)			49.18*** (11.69)
N	2,820	2,820	2,820	2,820	2,820	2,820
R ²	0.632	0.673	0.679	0.643	0.68	0.683

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Prices are in 2016 dollars using a quarterly GDP deflator

Results from specification 2, which incorporates a linear monthly time trend that accounts for increasing medallion values over time due to factors other than the control variables, are shown in column two. Incorporating this trend increases the magnitude of the coefficient estimates for the number of Uber drivers and wheelchair accessible or alternative fuel medallions. Under this specification, the coefficient estimate for medallions sold via auction suggests that medallions sold in this way sell for a higher amount than when transferred from person-to-person. It also increases the precision with which the coefficients for unemployment and gasoline prices are estimated. The unemployment rate is estimated to have a negative impact on medallion values as predicted. The coefficient estimate for gasoline prices suggests that gas prices are negatively related to medallions because an increase in the price of gasoline results in higher operating costs for taxi drivers.

The third column includes a quadratic monthly time trend variable. Adding a quadratic trend controls for the trend in medallion values over time but allows for a more flexible relationship between time and medallion value than a linear trend. The coefficient estimates for both the linear and quadratic the trend variables are statistically significant at the 1 percent level. All coefficient estimates follow predictions of the model with the exception of population—which is estimated to be negative—and the real interest rate—which is estimated without precision. Under this specification, one additional Uber driver is estimated to decrease the value of a taxi medallion by \$33.22 on average. One disadvantage of this specification is that it assumes the relationship between the number of Uber drivers and medallion values is constant across the number of Uber drivers.

Specifications 4, 5, and 6 add a quadratic term to the number of Uber drivers variable, which allows the estimated effect of additional Uber drivers to vary with the number of drivers. Specifications 5 and 6 are preferred over 4 because they employ a linear or quadratic monthly time trend, which improves estimation in a way analogous to moving from specification 1 to specifications 2 and 3. Specification 5 adds the quadratic term to the number of Uber drivers variable and a linear monthly time trend. Results from this specification closely mirror those of specification 3 in its estimates for wheelchair accessible medallions, alternative fuel medallions, independent medallions, auctioned medallions, population, unemployment, gasoline prices, and the real interest rate. This yields interesting results for the impact of Uber's presence on taxi medallion values. The coefficient estimates for this relationship are interpreted as follows:

Estimated model:

$$\begin{aligned}
 Med_Trans_Price_{it} &= -2,240,426 + 12.88(Num_drivers_t) - 0.00135(Num_drivers_t^2) \\
 &- 161,901 (WAC_{it}) - 186,267 (AltFuel_{it}) - 84,368(Independent_{it}) \\
 &+ 175,081(Auction_{it}) + \mathbf{X_t\beta_6} + 7,397 * t + \varepsilon_{it}
 \end{aligned}$$

Now, taking the derivative of the function with respect to $Num_drivers$:

$$\frac{\partial Med_Trans_Price}{\partial Num_Drivers} = 12.88 - 0.0027 (Num_drivers)$$

Solve for ∂Med_Trans_Price :

$$\partial Med_Trans_Price = [12.88 - 0.0027 (Num_drivers)] * \partial Num_Drivers$$

Using these coefficient estimates, the impact of Uber is non-negative until there are roughly 4,770 Uber drivers in the city.⁴³ This result makes intuitive sense. It is unlikely that Uber's presence has a large effect before Uber establishes a consumer base and becomes a credible threat to the taxi industry. Once Uber gains popularity, two things likely occur: (1) taxi drivers begin to experience customers substituting away from taxis and into Uber services, and (2) medallion holders begin to see Uber as a credible threat that, left unregulated, could have a large negative impact on the taxi industry as a whole.

Specification 6 incorporates a squared term on the number of Uber drivers and a quadratic monthly time trend. Here, the coefficients for the number of Uber drivers are interpreted analogous to specification 6:

$$\frac{\partial Med_Trans_Price}{\partial Num_Drivers} = -2.408 - 0.0021 (Num_drivers)$$

The coefficient estimate on the $Num_drivers^2$ term is estimated to be -0.00105 and is significant at the one-percent level. The coefficient estimate on $Num_drivers$ is estimated to be -2.408 but is not statistically significant. The coefficient on $Num_drivers$ is the intercept of the quadratic relationship between the number of Uber drivers and taxi medallion values. The lack of precision in its estimation is puzzling. By comparing specifications 5 and 6 it appears adding a quadratic monthly time trend creates this lack in precision. For this reason, incorporating both the quadratic term on the $Num_drivers$ variable and the quadratic monthly time trend may not be suitable for estimation. Due to the lack of statistical significance in specification 6 and because specification 5 results in

⁴³ Calculated by setting $\frac{\Delta Med_Trans_Price}{\Delta Num_drivers}$ equal to zero: $0 = 13.24 - 0.0028(number\ of\ Uber\ drivers)$
 $\rightarrow number\ of\ Uber\ drivers = 4,770.37$.

more conservative estimates of the losses attributed to the introduction and expansion of Uber, specification 5 is the preferred model for New York City.

A disadvantage to specifying a quadratic relationship between the number of Uber drivers and medallion values is that the coefficient estimates can only be interpreted with precision on a small interval, making aggregation of the effect cumbersome.⁴⁴

Nonetheless, interpreting the effect of changes in Uber's presence still yields meaningful results. Using results from specification 5, an increase from 10,000 to 15,000 Uber drivers in NYC results in a \$104,350 decrease in the value of a taxi medallion.⁴⁵ For perspective, based on my replication of Hall and Kruger's (2016) work (shown in figure 1), this increase in the number of Uber drivers in NYC took place from roughly August 2014 to December 2014. During this five-month period, I estimate medallion values to have decreased by \$104,350, a 14.6 percent decrease in price relative to 2013 average transfer prices.⁴⁶

The coefficient estimates on the other explanatory variables also yield interesting results. Wheelchair accessible medallions are estimated to sell for \$151,000 less on average than their non-restricted counterparts. This result is quite large in magnitude. Relative to the sample mean price of a medallion in NYC of roughly \$590,000, restricted medallions are sold for nearly 26 percent less than non-wheelchair accessible medallions. As mentioned previously, this decrease in price is likely driven by the increased costs associated with purchasing and operating vehicles that are acceptable for use under

⁴⁴ The aggregate effect of the expansion of Uber drivers is the summation of all one-unit (i.e., one-driver) increases to the number of Uber drivers up to its current amount. The effect aggregated to the medallion and industry level by city in table 8.

⁴⁵ Calculation: $\Delta \text{Med_Trans_Price} = [12.88 - 0.0027(12,500)] * (5,000) = - \$104,350$

⁴⁶ Annual average price per medallion in NYC in 2013 was \$714,347.56. 2013 was chosen for comparison because the number of Uber drivers does not exceed the approximate 4,800 mark at which Uber begins to have a negative effect on medallion prices until 2014.

wheelchair accessible medallions. Alternative fuel medallions sell for roughly \$180,000 less than non-alternative fuel medallion, which is similar in magnitude to the price difference of wheelchair accessible medallion at about 30 percent less than the sample mean transfer price in NYC. Similarly, independent medallions are estimated to sell for considerably lower amounts than corporate medallions in the city—nearly \$84,000, which represents a 14.2 percent decrease relative to the NYC sample mean transfer price. Again, this appears to be the result of a lack of growth opportunities for independent medallions and possible economies of scale enjoyed by corporate medallion holders. Medallions sold at auction yield a higher price than those transferred from person to person. This premium is estimated to be roughly 27 percent.

Unemployment is estimated to have a negative relationship with medallion values as predicted. A one-unit increase in the unemployment rate (e.g., an increase from an unemployment rate of 5 percent to 6 percent) is estimated to decrease medallion values by nearly \$8,000. Gasoline prices are estimated to have a negative relationship with medallion values as well. One-dollar increases in the price of a gallon of gasoline result in an estimated 6.7 percent decrease in the price of a medallion on average.⁴⁷ The estimated coefficient for population is of the opposite sign than predicted and suggests that an increase in population decreases medallion values. The coefficient estimate for real interest rate is imprecisely estimated.

One potential issue with the estimation of the effect of additional Uber drivers on medallion values is that the timing of Uber's entrance and the rate of expansion of the number of Uber drivers could be endogenous to taxi regulation and medallion values. The

⁴⁷ The 6.7 percent decrease is relative to the NYC sample mean.

endogeneity creates a simultaneity bias in the results. There are two possible strategies that Uber may follow when deciding which cities to enter, when to enter them, and how to expand. The first strategy is that Uber may enter into cities where the perspective profits are highest. Under this scenario, Uber will choose to enter high medallion values cities first because the potential profits are higher as high medallion values signal profits of medallion holders. The second possible strategy is to postpone entry into regulated cities because taxi companies in these cities are likely to fight the entrance of Uber to protect their medallion rents.

Preliminary research conducted by Rucker and Parker (2017) suggests that Uber enters and expands faster in cities with taxi regulation and high medallion values, which provides evidence that Uber enters new markets using the first strategy. The positive relationship between the timing of Uber's entry—and the nature of its expansion in that city—and taxi regulation allows me to sign the simultaneity bias (see Wooldridge 2012, 558-560). Consider the following two-equation structural model:

$$Medallion_values = \alpha_1 Uber + \beta_1 z_1 + u_1$$

$$Uber = \alpha_2 Medallion_values + \beta_2 z_2 + u_2$$

where *Medallion_values* are taxi medallion values, *Uber* is Uber's presence, and z_1 and z_2 are exogenous and thus uncorrelated with u_1 or u_2 . I then solve for *Uber* by substitution and under the assumption that $\alpha_2 \alpha_1 \neq 1$.⁴⁸

$$Uber = \frac{\alpha_2 \beta_1 z_1}{(1 - \alpha_2 \alpha_1)} + \frac{\beta_2 z_2}{(1 - \alpha_2 \alpha_1)} + \frac{(\alpha_2 u_1 + u_2)}{(1 - \alpha_2 \alpha_1)}$$

⁴⁸ Based on the results, $\alpha_2 \alpha_1 \neq 1$ as $\alpha_2 > 0$ and $\alpha_1 < 0$ and therefore $\alpha_2 \alpha_1 < 0$

Dropping z_1 from the equation for simplicity and assuming u_1 and u_2 are uncorrelated, I solve for the covariance of *Uber* and u_1 , which allows me to sign the bias:

$$\begin{aligned} Cov(Uber, u_1) &= [\alpha_2 / (1 - \alpha_2 \alpha_1)] E(u_1^2) \\ &= [\alpha_2 / (1 - \alpha_2 \alpha_1)] \sigma_1^2 \end{aligned}$$

where σ_1^2 is the variance of u_1 and $Var(u_1) > 0$, which implies the sign of the bias is the sign of $[\alpha_2 / (1 - \alpha_2 \alpha_1)]$ (Wooldridge 2012). Recall that $\alpha_1 < 0$ as *Uber* has a negative relationship with *Medallion_values* and $\alpha_2 > 0$ based upon the preliminary finding that Uber enters into markets with higher medallion values sooner and the number of drivers increases more rapidly in these areas (Rucker and Parker 2017), which implies $[\alpha_2 / (1 - \alpha_2 \alpha_1)] > 0$ and the bias is positive. A positive (or upward) bias in the estimate for α_1 —which estimates the effect of additional Uber drivers on medallion values—understates the true effect of additional Uber drivers on taxi medallion values. Therefore, the estimates in this paper are conservative and serve as a lower bound for the negative effect of Uber on taxi medallion values as the true effect is likely larger than estimated here.

Across all the specifications, the presence of Uber has a negative impact on the value of taxi medallions in NYC. Whether the model imposes a linear or quadratic relationship between the number of Uber drivers and the price of a taxi medallion value, the effect of numerous Uber drivers in NYC on medallion values is negative and both statistically and economically significant. Above, the decrease in price associated with an increase from 10,000 to 15,000 Uber drivers was calculated to be \$104,350, or a 14.6 percent decrease relative to the 2013 mean transfer price in NYC. This effect increases in magnitude over time. Moving from 25,000 to 30,000 Uber drivers—a change

representative of conditions in NYC from September 2015 to December 2015—results in a decrease of nearly \$307,000.⁴⁹ In those four months alone, I estimate that Uber reduced medallion transfer prices by nearly 43 percent relative to the 2013 mean transfer price in the city of about \$714,000.⁵⁰

Chicago

Results from Chicago estimations are presented in table 4. The six columns again represent six different specifications. Column one represents the simplest, most naïve specification. Here, medallion values are regressed on the number of Uber drivers and the set of control variables without the inclusion of a time trend variable. While the signs of the majority of the coefficient estimates are consistent with predictions under this specification, adding a monthly or quadratic time trend—which accounts for trends in medallion values over time—increases the statistical significance of the coefficient estimates. The second column shows results from the model with the addition of a linear monthly time trend variable to the estimation. Under this specification, all variables are of the predicted sign and most are statistically significant with the exception of the real interest rate. Specification 3 adds a quadratic monthly time trend variable. Results under this specification are very similar in both precision and magnitude to those of specification 2. Although the interpretation of coefficient estimates is nearly identical when comparing specification 2 and 3, specification 3 allows more flexibility in the

⁴⁹ Calculation: $\Delta \text{Med_Trans_Price} = [12.88 - 0.0027(27,500)] * (5,000) = - \$306,850$

⁵⁰ The annual mean transfer price in NYC was \$714,347.56 in 2013.

pattern of medallion values in Chicago over time. Therefore, specification 3 is preferred to specifications 1 or 2.⁵¹

Table 4: Effect of Uber on taxi medallion values: Chicago

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-2.916*** (0.642)	-12.68*** (1.175)	-12.57*** (1.672)	-1.518 (1.310)	-17.91*** (1.554)	-22.03*** (2.297)
Number of Uber drivers ²				0.00 (0.00)	0.00025*** (0.00)	0.00034*** (0.00)
Auction	5,207 (5,993)	15,110*** (5,987)	14,852*** (6,332)	5,565 (6,014)	14,335*** (5,996)	19,043*** (6,296)
Population	8.243*** (0.122)	1.516*** (0.301)	1.559*** (0.471)	8.163*** (0.149)	1.484*** (0.302)	0.643* (0.478)
Unemployment rate	16,353*** (440.5)	-1,953** (1,008)	-2,036** (1,033)	16,425*** (443.8)	-3,036*** (1,028)	-1,820** (1,028)
Gasoline price per gallon	-13,189*** (1,913)	-4,313*** (1,772)	-4,361*** (1,746)	-12,675*** (1,975)	-5,670*** (1,768)	-5,236*** (1,754)
Real interest rate	-12,205*** (598.9)	-20.16 (782.3)	9.084 (787.4)	-12,090*** (616.8)	141.0 (787.2)	-367.2 (785.7)
Linear monthly time trend		3,598*** (172.5)	4,569 (6,955)		3,762*** (176.6)	-15,021** (6,873)
Quadratic monthly time trend			-0.808 (5.819)			15.68*** (5.767)
N	3,398	3,398	3,398	3,398	3,398	3,398
R ²	0.781	0.812	0.812	0.781	0.813	0.814

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator

⁵¹ The coefficient estimates for both trend variables are statistically insignificant under specification 3, however.

Under specification 3, a one-driver increase in the number of Uber drivers in Chicago is estimated to decrease the value of a taxi medallion by \$12.57—an estimate statistically significant at the one percent level. For perspective, in December 2015, there were roughly 33,000 Uber drivers in Chicago. Using the coefficient estimate from specification 3, this implies that as of December 2015, each medallion values had decreased by \$414,810. An effect this large in Chicago is not feasible, however. A decrease in medallion values of \$414,810 is a decrease significantly larger than any of the monthly average medallion transfer prices in Chicago in the entire sample from January 2007 – December 2015.⁵² Such a result suggests that the relationship between the number of Uber drivers and medallion values may not be linear. To address this, specifications 4, 5, and 6 add a quadratic term to the number of Uber drivers, allowing the effect of Uber on taxi medallion values to change as the number of Uber drivers changes.

Specification 4 adds the quadratic term to the number of Uber drivers but does not control for any trends in the value of taxi medallions over time. The coefficient estimates on both the number of Uber drivers and the number of Uber drivers squared are small in magnitude and lack statistical significance. Once a trend is accounted for—either linear or quadratic—the coefficients for both variables increase in magnitude and statistical significance. Specification 5—which fits a linear monthly trend to medallion values over time—and specification 6—which fits a quadratic trend to medallion values—yield similar results. Interpretation of the coefficient estimates uses the same method as used above for the NYC results.

⁵² Auction sale prices are dropped when calculating monthly mean medallion transfer prices.

Coefficient estimates from specification 5 yield the following interpretation:

$$\partial Med_Trans_Price = [-17.91 + 0.0005 (Num_drivers)] * \Delta Num_Drivers$$

Coefficient estimates from specification 6 yield:

$$\partial Med_Trans_Price = [-22.03 + 0.00068 (Num_drivers)] * \Delta Num_Drivers$$

Both specifications suggest that the effect of additional Uber drivers on medallion values decreases over time and eventually becomes zero at a certain number of Uber drivers.

According to the estimates from specification 5 and 6, the effect dissipates after roughly 33,000 to 36,000 Uber drivers enter the market. The number of Uber drivers in Chicago as of December 2015 was roughly 31,700.^{53,54}

Although both specifications 5 and 6 yield very similar results, coefficient estimates for the control variables under specification 5 are estimated with more precision than under specification 6. For this reason specification 5 is this preferred specification for Chicago. Under specification 5, the signs of the coefficient estimates are consistent with the predicted relationship between the other explanatory variables and medallion values. Medallions sold at auction are estimated to sell for roughly \$14,000 more than medallions transferred from person to person. This represents a 6.7 percent increase in price relative to the Chicago sample mean transfer price. This result is smaller than the result in NYC, the difference might be driven by differences in the number of bidders that participated in the auctions in each city. Auctions in Chicago collected significantly fewer bids than auctions in NYC and because the increase prices due to auctions is driven

⁵³ Calculated by setting $\frac{\Delta Med_Trans_Price}{\Delta Num_drivers}$ equal to zero: $0 = -22.03 - 0.00068(number\ of\ Uber\ drivers,)$
 $\rightarrow number\ of\ Uber\ drivers = 32,397.$

⁵⁴ Calculated by setting $\frac{\Delta Med_Trans_Price}{\Delta Num_drivers}$ equal to zero: $0 = -17.91 - 0.0005(number\ of\ Uber\ drivers,)$
 $\rightarrow number\ of\ Uber\ drivers = 35,820$

by the number of bidders, the effect should be smaller in Chicago than the effect in NYC. Population has a positive relationship with medallion values. Coefficient estimates suggest that an increase of 10,000 people in the population of Chicago would result in a near \$15,000 increase in the average price of a medallion.

Unemployment and gasoline prices have negative relationships with medallion values. A one-unit increase in the unemployment rate decreases medallion values by just over \$3,000—a 1.4 percent decrease relative to the sample mean transfer price in Chicago. A one-dollar increase in the price of a gallon of gasoline is estimated to reduce medallion values by \$5,670 on average, a roughly 2.6 percent decrease relative to the sample mean transfer price. Similar to the results from NYC, the real interest rate does not have a clear relationship with medallion values. Under specification 5 the coefficient estimate is small in magnitude and statistically insignificant.

As mentioned previously, when using quadratic terms in an OLS regression, the estimated marginal impacts of Uber drivers vary with the number of drivers and the coefficients can only be interpreted with precision on small intervals. According to the coefficient estimates for the number of Uber drivers from specification 5, an increase from 10,000 to 15,000 Uber drivers results in a \$58,000 decrease in the value of a medallion.⁵⁵ As the number of Uber drivers increase, this effect becomes smaller in magnitude. Moving from 20,000 Uber drivers to 25,000 results in a decrease of roughly \$33,000.⁵⁶ Relative to the sample mean transfer price in Chicago, these estimates represent 27.1 and 15.5 percent decreases in medallion values, respectively.

⁵⁵ Calculation: $\Delta \text{Med_Trans_Price} = [-17.91 + 0.0005(12,500)] * (5,000) = -\$58,300$

⁵⁶ Calculation: $\Delta \text{Med_Trans_Price} = [-17.91 + 0.0005(22,500)] * (5,000) = -\$33,300$

Boston

Estimations for the city of Boston follow the same progression across specifications as those of NYC and Chicago. Again, specifications 1 through 3 assume a linear relationship between the number of Uber drivers and medallion values.

Specification 1 does not account for a trend in medallion values over time. Specification 2 adds a linear trend to medallion values over the sample period. Specification 3 fits a quadratic time trend. Specifications 4-6 add a quadratic term to the number of Uber drivers. Similar to specifications 1, 2, and 3, specifications 4, 5, and 6 vary by the time trend variables used in the estimations. Specification 4 does not incorporate either of the time trend variables, specification 5 assumes a linear time trend, and specification 6 assumes a quadratic time trend. As discussed earlier, a linear relationship between the number of Uber drivers and medallions may not be sensible. The first few Uber drivers in a city might not have much of an impact on the value of taxi medallions. But after Uber gains popularity in an area, this effect might become larger. Specification 6 is the preferred specification for Boston because it allows for variability in the effect of an additional Uber driver as the number of drivers change and it incorporates linear and quadratic monthly time trends—both of which are statistically significant.

Under specification 6, the change in medallion transfer price—i.e., the change in medallion value—attributed to a change in the number of Uber drivers can be calculated as follows:

$$\partial Med_Trans_Price = [-21.84 - 0.0048(Num_drivers)] * \partial Num_Drivers$$

From September of 2013 to May of 2014, the number of Uber drivers in Boston increased from approximately 1,000 drivers to 5,000 drivers. This increase of 4,000 drivers is

associated with a \$145,000 decrease in medallion transfer prices.⁵⁷ Relative to the sample mean of Boston, this is a 27.6 percent reduction in medallion values. This effect increases as the number of Uber drivers increase. An increase in the number of Uber drivers from 5,000 to 10,000—as was the case in Boston from May 2014 to February 2015—is associated with a \$289,200 decrease in medallion values, a 55.1 percent decrease relative to the sample mean.⁵⁸

Table 5: Effect of Uber on taxi medallion values: Boston

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-33.00*** (3.168)	-38.91*** (2.895)	-60.19*** (2.604)	9.930** (4.829)	5.304 (4.293)	-21.84*** (5.075)
Number of Uber drivers ²				-0.0035*** (0.00031)	-0.0037*** (0.00032)	-0.0024*** (0.00033)
Restricted medallion	-112,282*** (22,248)	-97,896*** (22,126)	-82,867*** (14,220)	-108,587*** (18,953)	-91,324*** (18,762)	-85,535*** (14,585)
Population	8.040*** (0.599)	1.771 (1.503)	-2.449** (1.359)	6.174*** (0.614)	-1.362 (1.437)	-2.532** (1.363)
Unemployment rate	-19,290*** (5,547)	-16,021*** (4,949)	-17,320*** (4,602)	-23,779*** (5,435)	-20,152*** (4,521)	-19,392*** (4,321)
Gasoline price per gallon	-7,270 (10,805)	-39,998*** (10,178)	16,837* (12,186)	-6,380 (9,408)	-45,136*** (8,697)	-12,629 (12,028)
Real interest rate	16,705*** (2,209)	13,200*** (2,085)	-8,492*** (2,712)	13,588*** (2,005)	9,259*** (1,957)	-1,059 (2,632)
Linear monthly time trend		6,125*** (1,106)	-277,618*** (27,611)		7,263*** (1,018)	-146,349*** (29,881)
Quadratic monthly time trend			230.7*** (22.58)			124.6*** (24.25)
N	266	266	266	266	266	266
R ²	0.844	0.860	0.918	0.902	0.923	0.932

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Prices are in 2016 dollars using a quarterly GDP deflator

⁵⁷ Calculation: $\Delta \text{Med_Trans_Price} = [-21.84 - 0.0048(3,000)] * (4,000) = -\$144,960$

⁵⁸ Calculation: $\Delta \text{Med_Trans_Price} = [-21.84 - 0.0048(7,500)] * (5,000) = -\$289,200$

Under specification 6, coefficient estimates for the control variables yield results consistent with predictions. Restricted medallions—wheelchair accessible medallions specifically for Boston—are transferred for lower amounts on average.⁵⁹ The difference is an estimated \$85,535 and is significant at the 1 percent level. This implies that wheelchair accessible medallions are transferred for 16.3 percent less than unrestricted medallions relative to the sample mean for Boston. The unemployment rate has a negative relationship with medallion values. A one-unit increase in the unemployment rate is associated with a \$19,392 reduction in medallion values. The coefficient estimate for population is of the opposite sign than predicted. It is unlikely that an increase in population would lead to a decrease in medallion values. Population only becomes negative and significant once the quadratic time trend is added to the model. The sign and magnitude of the coefficient estimates are not sensitive to the exclusion of population, however. Coefficient estimates for gasoline prices and the real interest rate are not statistically significant, although they are of the predicted sign.

Across all specifications, the number of Uber drivers has a negative impact on medallion values.⁶⁰ When the relationship between the number of Uber drivers and medallion values is specified to be quadratic, this marginal effect of an additional Uber driver increases as the number of drivers increase. Using results from specification 6, the increase from 5,000 to 10,000 drivers in Boston that occurred from May 2014 to February 2015 decreased medallion values by roughly \$290,000, which is roughly a 55 percent decrease relative to the sample mean.

⁵⁹ Boston does not have alternative fuel medallions.

⁶⁰ Although the effect is not initially negative under specifications four and five, it becomes negative as the number of drivers increases.

Philadelphia

Table 6 shows the results for Philadelphia. Similar to the other cities, specifications 1-3 assume a linear relationship between the number of Uber drivers and medallion values, while specifications 4-6 assume a quadratic relationship. Differences across specifications are similar to those of the other sample cities. In comparing specifications to determine the preferred method, the time trend variables are always statistically significant when added. Therefore, specifications that incorporate both linear and quadratic monthly time trend variables (i.e., specifications 3 and 6) are preferred.

Table 6: Effect of Uber on taxi medallion values: Philadelphia

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-22.77*** (3.321)	-27.56*** (3.145)	-31.74*** (3.113)	18.92** (8.537)	-0.207 (9.484)	-14.11 (9.935)
Number of Uber drivers ²				-0.0050*** (0.0011)	-0.0032*** (0.0011)	-0.0020** (0.0012)
Auction (restricted medallion)	-311,464*** (25,352)	-314,222*** (24,853)	-317,212*** (24,645)	-356,651*** (27,783)	-343,211*** (28,146)	-334,995*** (28,297)
Population	5.405*** (0.117)	2.417*** (0.380)	1.483*** (0.370)	4.863*** (0.139)	2.316*** (0.371)	1.532*** (0.372)
Unemployment rate	-15,174*** (1,392)	-12,021*** (1,374)	-5,139** (1,998)	-9,992*** (1,526)	-8,933*** (1,490)	-4,038** (2,094)
Gasoline price per gallon	-960.2 (3,356)	1,654 (3,098)	-1,301 (2,996)	4,943* (3,378)	5,253** (3,129)	1,309 (3,014)
Real interest rate	-1,457* (938.9)	713.1 (919.2)	-1,406* (974.5)	-1,156 (927.1)	726.8 (918.7)	-1,141 (974.5)
Linear monthly time trend		2,633*** (330.6)	-17,208*** (4,782)		2,414*** (343.2)	-14,947*** (4,761)
Quadratic monthly time trend			16.76*** (3.980)			14.74*** (3.968)
N	653	653	653	653	653	653
R ²	0.846	0.854	0.857	0.849	0.855	0.857

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator

Using the coefficient estimate for the number of Uber drivers from specification 3, one additional Uber driver is estimated to decrease medallion values by roughly \$32.00. Aggregated by the most current number of drivers in Philadelphia from December 2015 (7,291 drivers), this amounts to about a \$251,000 decrease in medallion values on average.⁶¹ Unlike in Chicago, this result is feasible—although quite large—compared to the mean average transfer price in Philadelphia of about \$256,000. Nonetheless, assuming the relationship between the number of Uber drivers and medallion values is linear—i.e., constant across the number of drivers—may not be justifiable, especially when considering the results from the other sample cities. Therefore, specification 6 is the preferred specification for Philadelphia.

Specification 6 adds a quadratic term for the number of Uber drivers to the model estimated in specification 3. Coefficient estimates suggest that the negative effect of an additional Uber driver increases as the number of drivers increase. Analogous to the other sample cities, coefficient estimates on the number of Uber drivers can be interpreted as follows under specification 6:

$$\partial \text{Med_Trans_Price} = [-14.11 - 0.004(\text{Num_drivers})] * \partial \text{Num_Drivers}$$

From September 2014 to February 2015, the number of Uber drivers in Philadelphia increased from roughly 1,000 to 3,000. According to estimates from specification 6, this increase of 2,000 drivers is associated with about a \$44,000—or 17.27 percent relative to the sample mean—decrease in medallion values.⁶² Coefficient estimates for the number of Uber drivers and the number of Uber drivers squared are significant at the 10 and 5

⁶¹ Calculation: aggregate effect = effect of one additional Uber driver * number of Uber drivers in December 2015 → aggregate effect = $-31.74 * 7,921 \rightarrow$ aggregate effect = \$251,412.54.

⁶² Philadelphia sample mean transfer price is \$256,040.50. Calculation: $\Delta \text{Med_Trans_Price} = [-14.11 - 0.004(2,000)] * (2,000) = -\$44,220$

percent level. The low level of statistical significance here might be due to the low sample size despite the long time period of the sample. The low number of medallion transfers—particularly toward the end of the sample time period from roughly 2014 to 2015—might be reducing the predictive power of the model.

Coefficient estimates for control variables generally have the predicted sign in this specification as well. While medallions sold at auction appear to sell for less than those transferred, all medallions sold at the 2015 auctions in Philadelphia were wheelchair accessible medallions. The auction indicator variable is perfectly collinear to a wheelchair accessible medallion indicator variable because the auction of these medallions was the first issuance of any wheelchair accessible medallions in Philadelphia. Because both variables are represented in the auction variable, the coefficient estimate is picking up the effect of a medallion being sold by auction *and* that of a medallion being wheelchair accessible. If we assume auctions would yield higher prices than person-to-person transfers in Philadelphia as they do in other cities, the reduction in value associated with wheelchair accessible medallion must outweigh the increase in price associated with auctioning the medallions.

The auction in Philadelphia, however, was not conducted in the same manner as auctions in NYC and Chicago and therefore may not result in higher sale prices. In Philadelphia, bidders are required to specify what medallion they are bidding for by listing the medallion number on their bid. Because of this structure, some of the highest bids from the auctions did not result in the acquisition of a medallion. As such, auctioned medallions may not have sold for any higher of a price—possibly even a lower price—than medallions that were transferred between two individuals at that time. The

coefficient estimate for the auction/restricted medallions is negative, statistically significant, and large. Without the occurrence of another auction or the transfer of wheelchair accessible medallions from person-to-person, I am unable to determine which part of the coefficient estimate is due to medallions being sold via auctions and which part is due to the medallion being a wheelchair accessible medallion.

As predicted, population is estimated to have a positive relationship with medallion values. An increase of 10,000 people in the population of Philadelphia is associated with a \$1,532 increase in medallion values. This estimate is significant at the one-percent level. Unemployment is negatively related to medallion values. A one-unit increase in the unemployment rate in Philadelphia is associated with a \$4,038 decrease in medallion values. Coefficient estimates for gasoline prices and the real interest rate are imprecisely estimated.

All specifications suggest that Uber's presence has a negative impact on medallion values. Allowing this relationship to vary as the number of Uber drivers changes suggests that the negative effect of an additional Uber driver increases (i.e., becomes more negative) as the number of Uber drivers increases. As calculated above, an increase from 1,000 drivers to 3,000 drivers is associated with about a 13 percent decrease in medallion values relative to the Philadelphia sample mean.⁶³ Increasing the number of drivers from 4,000 to 6,000—representative of the increase that occurred in Philadelphia from April to July in 2015—is associated with a decrease of about \$68,000

⁶³ Philadelphia sample mean transfer price is \$256,040.50

in medallion values.⁶⁴ This translates to a 26.6 percent decrease relative to the Philadelphia sample mean.

Discussion

The effect of Uber across cities is similar in that it is estimated to be negative but varies in its relationship to the number of Uber drivers. In NYC, there is initially no negative effect on medallion values. The effect only appears after roughly 5,000 Uber drivers are in the city. The negative effect on medallion values then increases in magnitude. Alternatively, the negative effect of Uber of additional Uber drivers is estimated to begin immediately and then decrease to zero once the number of Uber drivers reaches roughly 35,000 in Chicago. Boston and Philadelphia experience the negative effect of an additional Uber driver immediately and this effect becomes more negative as the number of drivers increase.

A potential explanation of these differences involves variation in average medallion values and variation in the amount of growth in Uber drivers across cities. It is possible that cities with higher average medallion values prior to Uber's entrance do not initially feel the negative effect of additional Uber drivers and the effect only appears after the number of Uber drivers is large enough that the demand for taxis is noticeably affected—as appears to be the case in NYC. Alternatively, cities with low average medallion values might see a negative effect right away as results suggest for Chicago and Philadelphia. The differences in the change in effect as the number of Uber drivers increase might be driven by the growth of Uber in those cities. Chicago experiences the

⁶⁴ Calculation: $\Delta \text{Med_Trans_Price} = [-14.11 - 0.004(4,000)] * (2,000) = -\$68,220$

highest growth in the number of Uber drivers from June 2012 to December 2015 and is the only city to show the negative effect of additional drivers dissipating over time. It is possible that similar results might occur for NYC, Boston, and Philadelphia once Uber's presence increases in those cities.⁶⁵

⁶⁵ Although the growth of Uber is quite comparable in NYC and Chicago, NYC medallion values are much higher on average than Chicago. This suggests that growth in Uber would need to increase before results might change to be similar to Chicago.

POOLED SAMPLE ESTIMATION

Empirical Model

Measuring the same relationship as measured above for each city, but now using a pooled sample to correct for unobservable shocks that may have affected all of the sample cities—such as the great recession or federal policies affecting inputs to the taxi industry. To measure this relationship, I pool all the cities together into one sample and estimate the following fixed effects model:

$$(2) \text{ Med_Trans_Price}_{ijt} = \beta_0 + \beta_1 \text{Num_Drivers}_{jt} + \beta_2 \text{WAC}_{ijt} + \beta_3 \text{AltFuel}_{ijt} + \beta_4 \text{Independent}_{ijt} + \beta_5 \text{Auction}_{ijt} + \mathbf{X}_{jt}\boldsymbol{\lambda} + \phi_j * t + \theta_j * t^2 + \omega_j + \varepsilon_{it}$$

Analogous to equation (1), $\text{Med_Trans_Price}_{ijt}$ is the transfer price of transfer i in city j at time t . Num_Drivers_{jt} is the number of active Uber drivers in city j at time t . Auction_{ijt} is a binary variable equal to one if transfer i in city j at time t is sold via auction. WAC_{ijt} is another binary variable equaling one if transfer i in city j at time t is a wheelchair accessible medallion. Similarly, AltFuel_{ijt} is an indicator variable if transfer i in city j at time t is the transfer or sale of an alternative fuel medallion. $\mathbf{X}_{jt}$ is the same vector of controls—unemployment, population, gasoline prices, and real interest rates—as in equation (1) for city j at time t . $\phi_j * t$ and $\theta_j * t^2$ represent city specific quadratic time trends accounting for trends in medallion values in the each city over time. ω_j represents city fixed effects, correcting for time invariant differences across cities. ε_{it} is the error term. Predictions for coefficient estimates are equivalent to those of the estimations by city.

In addition to employing city fixed effects to address possible differences across cities, standard errors are clustered at the city level. Clustering at the city level corrects for heteroskedasticity—i.e., differences in variance—in the errors across cities. If errors do vary across cities, failing to cluster standard errors at the city level results in smaller estimated standard errors, which could lead to false precision in coefficient estimates. Clustering at the city level leads to conservative estimates in terms of statistical significance.

Results

Table 7 shows results from the pooled sample. Six different specifications are estimated. Specification 1 regresses medallion values on the number of Uber drivers and the control variables without city fixed effects or a time trend. Under this specification, the coefficient estimates do not make much intuitive sense. The only coefficient estimates with signs that agree with predictions are population and the real interest rate and these coefficients are estimated imprecisely. Specification 2 adds a linear monthly time trend variable to the model, estimating a linear time trend for entire pooled sample. Adding the linear time trend to the model results in estimates that are largely consistent with predictions but the estimates still lack the desired precision.

Specification 3 allows for flexibility in the shape of the time trend by adding a quadratic monthly time trend variable to the model. Specification 4 adds city fixed effects in addition to a quadratic monthly time trend. Adding city fixed effects accounts for time invariant differences in medallion values across cities.⁶⁶ Adding this element to the model

⁶⁶ Adding city fixed effects allows for different vertical intercepts for each city in the sample.

is justified because the average medallion values vary across cities. For example, as can be seen in figure 6, NYC exhibits higher monthly average medallion values than the other sample cities in virtually every month, while Chicago exhibits lower average medallion values than the other cities in every month. Adding city level fixed effects increases the precision of the coefficient estimates but assumes that all cities have the same quadratic monthly time trend in medallion values over time. Inspection of figure 6—which plots the monthly average transfer prices by city across time—suggests that the trends do appear to be similar but not identical. Specifications 5 and 6 add city specific linear and quadratic time trends to the model—thereby estimating a different trend for each city. Across these two specifications, coefficient estimates are markedly similar in sign, magnitude, and statistical significance. Because medallion values appear to have more of a quadratic relationship with time than a linear one and because the quadratic trend is statistically significant, specification 6 is preferred to specification 5.

Coefficient estimates under specification 6 suggest that one additional Uber driver in a given city is associated with an approximate \$16.00 decrease in the value of a medallion. This result is significant at the 1 percent level. Similar to results from the estimations by city, wheelchair accessible medallions, alternative fuel medallions, and independent medallions sell for less than unrestricted or corporate medallions. The coefficient for wheelchair accessible medallions is estimated to be - \$100,189 and is significant at the 10 percent level, implying wheelchair accessible medallions sell for roughly 26 percent less than non-restricted medallions relative to the pooled sample mean.⁶⁷ Alternative fuel medallions sell for roughly \$155,000 less than non-alternative

⁶⁷ The pooled sample mean transfer price is \$380,126.60.

fuel medallions. Independent medallions sell for roughly 24 percent less than corporate medallions, a result that is significant at the 1 percent level.

Table 7: Effect of Uber on taxi medallion values: Pooled Sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Uber drivers	23.56*** (2.627)	-22.98** (7.275)	-19.86** (5.788)	-15.93*** (2.086)	-15.74*** (2.130)	-16.44*** (2.360)	-29.26*** (1.464)
Chicago X Number of Uber drivers							10.19*** -0.648
Boston X Number of Uber drivers							-27.11*** -0.967
Philadelphia X Number of Uber drivers							-14.81** -3.914
Wheelchair accessible medallion	238,919** (60836)	-8,139 (111983)	-51,767 (108289)	-79,672* (41935)	-97,905* (47783)	-100,189* (47639)	-105,193** (32309)
Alternative fuel medallion	-25,692 (29183)	-135,514** (47112)	-174,440** (52577)	-132,836** (38165)	-152,528** (44020)	-154,974** (43657)	-157,252*** (28085)
Independent medallion	99,847 (144104)	26,414 (97224)	26,194 (91837)	-92,249*** (4170)	-89,649*** (5856)	-89,159*** (5899)	-88,360*** (4861)
Auction	-85,129** (27139)	118,699* (61388)	176,942** (71959)	108,331* (51680)	135,568* (60196)	137,635* (59716)	115,208** (44779)
Population	0.0523* (0.025)	0.0603** (0.015)	0.0604** (0.014)	0.471*** (0.040)	0.239 (0.185)	0.123 (0.203)	-1.089*** (0.104)
Unemployment rate	17,656 (13498)	-33,491* (15258)	-36,933** (15445)	-8,660 (5407)	-8,125* (4072)	-7,596* (4043)	-4,233 (3282)
Gasoline price per gallon	28,725 (26481)	-70,415* (32779)	-72,207* (33048)	-8,973 (10551)	-10,503 (11309)	-10,939 (11624)	-13,095 (13553)
Real interest rate	-14,085 (11246)	-5,282 (4570)	-5,128 (4132)	5,610 (4043)	4,488* (2707)	4,002 (2524)	933 (1023)
Linear monthly time trend	No	Yes	Yes	No	No	No	No
Quadratic monthly time trend	No	No	Yes	Yes	No	No	No
City specific monthly linear time trend	No	No	No	No	Yes	No	Yes
City specific monthly quadratic time trend	No	No	No	No	No	Yes	Yes
City fixed effects	No	No	No	Yes	Yes	Yes	Yes
N	7,107	7,107	7,107	7,107	7,107	7,107	7,107
R ²	0.615	0.774	0.777	0.847	0.848	0.848	0.853

Notes: Robust standard errors clustered at the city level in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator, Observations from Philadelphia's 2015 auctions are dropped.

Auctions are estimated to result in higher prices than transfers from person-to-person. Population and gasoline prices are estimated to be of the correct sign but are not statistically different from zero. Unemployment is again estimated to have a negative relationship with medallion values. Estimates suggest that a one-unit increase in the unemployment rate of a city would decrease the value of medallions by about \$7,600. This result is significant at the 10 percent level. Standard errors are clustered at the city level to control for heteroskedasticity in the errors across cities. To examine whether this is justified, I plot the predicted errors from specification 6 on the set of control variables, across cities, and across time. Plots are displayed in Appendix D. A visual examination of the plots suggests that the standard errors vary by city and by population. Because population differences are driven by the city, clustering at the city level accounts for these differences along with the differences across cities.

Appendix C shows and discusses results for the pooled sample with the addition of the squared term on the number of Uber drivers. Using this model leads to imprecise estimates and thus is not the model of choice for the pooled sample. A likely explanation of the imprecise estimates is that the quadratic relationship estimated between the number of Uber drivers and medallion values is quite different across cities. When the sample is pooled, the same quadratic relationship is estimated for *all* cities unless interaction terms of the number of Uber drivers across cities are included. As shown in Appendix C, including interaction terms by city and thus allowing the effect of Uber to vary across cities, results in statistically significant estimated coefficients for the impact of Uber on medallion values. It appears that the length of time Uber has been in a city, the growth in the number of drivers, and average medallion values in general across cities may be

causing these differences in the relationship between Uber's presence and medallion values across cities.

To address these cross-city differences, specification 7 includes interaction terms between city dummy variables and the number of Uber drivers. Including these interaction terms allow the linear relationship between the number of Uber drivers and medallions to differ across each of the sample cities. NYC is the omitted city, and thus the coefficient estimates for the number of Uber drivers represents NYC's specific linear relationship. Under specification 7, results suggest that the effect of additional Uber drivers on medallion values varies across cities.⁶⁸ One additional Uber driver is estimated to decrease medallion values by \$29.26 in NYC. The effect is less in Chicago with an estimated \$19.07 decrease in medallion values for each additional Uber driver in Chicago. Philadelphia and Boston are estimated to have larger decreases in average medallion values due to additional Uber drivers in each city. Boston is estimated to experience a \$56.37 decrease in medallion value per one driver increase in the number of Uber drivers. The estimated decrease in medallion values in Philadelphia is \$44.07 per additional Uber driver. While this model does not allow the effect of additional Uber drivers to change as the number of drivers changes, specification 7 accounts for the differences in the effect across cities—differences which are estimated to be statistically significant and large in magnitude.

The differences in the magnitude of the effect of the introduction and expansion of Uber on medallion values across cities is important as it clearly illustrates the inappropriateness of generalizing the effect for all cities. An alternative approach to

⁶⁸ Coefficient estimates for the three interaction terms are jointly significant at the 1 percent level.

normalizing the effect across cities is explored in Appendix E where the ratio of Uber drivers to medallions is used as an explanatory variable instead of simply the number of drivers.

AGGREGATION OF RESULTS

This chapter presents aggregate results of the effect of the introduction and expansion of Uber on taxi medallion values in each of the four cities. Results include total losses per medallion, the percentage decrease relative to average medallion values, and the estimated total industry loss. To obtain an estimate of the aggregate effect of Uber on taxi medallions for a given city, I sum the marginal effects of one-unit increases in Uber drivers using the city specific quadratic estimates.⁶⁹ To do so, I use the following formula:

(3) *Aggregate Effect_i*

$$= \left[\sum_{k=0}^n (Num_drivers\ coefficient_i + (2 * Num_drivers^2\ coefficient_i * k)) \right] * (number\ of\ taxi\ medallions_i)$$

where *Num_drivers coefficient_i* is the coefficient estimate for the number of Uber drivers term under the preferred model for city *i*, *Num_drivers² coefficient_i* is the coefficient estimate for the number of Uber drivers squared term under the preferred model for city *i*, *n* is the number of Uber drivers in city *i*, and *number of taxi medallions_i* is the number of taxi medallions in city *i*. Equation (3) represents the summation of the effect of all one driver increases in Uber drivers up to the number of Uber drivers in a city using results from the preferred quadratic model for each city. For example, the preferred specification for NYC is specification 5. Using results

⁶⁹ Recall the effect of one-unit increases in the number of Uber drivers changes as the number of Uber drivers change. Therefore, the aggregate effect is the summation of all the one-driver marginal effects, which is calculated using equation (3).

from column 5 in table 3, the aggregate effect of the introduction and expansion of Uber in NYC is calculated using the following equation:

$$Aggregate\ Effect_{NYC} = \left[\sum_{k=0}^{28,326} (12.88 + (2 * (-0.00135) * k)) \right] * (13,333)$$

Table 8 summarizes the aggregate results by city. Results are calculated using the coefficient estimates from specification 5 in table 3 for NYC, specification 5 in table 4 for Chicago, specification 6 in table 5 for Boston, and specification 6 in table 6 for Philadelphia.

Table 8: Aggregated Effect of Uber on taxi medallion values by city

Variables	NYC	Chicago	Boston	Philadelphia
Effect of one additional Uber driver	12.88 - 0.0027 x (# of drivers)	-17.91 + 0.0005 x (# of drivers)	- 21.48 - 0.0048 x (# of drivers)	-14.11 - 0.004 x (# of drivers)
Number of Uber drivers ¹	28,326	31,787	13,056	7,921
Estimated effect of Uber per medallion	(718,376)	(316,712)	(694,214)	(237,280)
Percentage decrease in average medallion values ²	68.5%	87.9%	100.02%	50.6%
Number of taxi medallions ³	13,333	6,904	1,825	1,629
Aggregate effect of Uber on taxi medallion values	\$9.58 billion	\$2.19 billion	\$1.27 billion	\$386.5 million

Notes: (1) Number of Uber drivers value is the most recent observed value in the data for each city. (2) Relative to the highest annual average medallion price in each city the sample. (3) Number of taxi medallions are as of December 2015. Aggregate values were calculated using equation (3).

Aggregating the results in such a way produces some interesting results. First, the average decrease in medallion values is calculated for each city. On a per medallion basis, the average decrease in medallion values associated with the introduction and expansion of Uber is highest in NYC with an estimated decrease of over \$718,000 per medallion. Boston, Chicago, and Philadelphia follow in magnitude of the decrease with estimated losses to medallion values of approximately \$694,000, \$317,000, and \$237,000. Comparing the estimates to average medallion values in each city normalizes the differences in the magnitude of the estimates across cities by estimating the percentage change in medallion values.⁷⁰

The percentage decrease in medallion values in NYC is an estimated 68.5% relative to the 2013 annual average medallion value, indicating that the introduction and expansion of Uber decreased medallion values by at least 68.5 percent by the close of 2015.⁷¹ Philadelphia medallion values are estimated to have decreased by 50.6 percent as a result of the introduction and expansion of Uber. Chicago and Boston exhibit high percentage decreases in medallion values relative to their maximum annual average medallion values with 87.9 percent and 100.02 percent. These results are large in magnitude but not implausible. The decrease in medallion values is estimated with the incorporation of the overall trend in medallion values over time and other variables that affect medallion values. The high results indicate that, in the absence of the entry of

⁷⁰ Percent changes in medallion values are relative to the highest annual averages for each city in the sample. The highest annual averages occurred in 2013 for NYC and Chicago with annual average medallion values of approximately \$1.05 million in NYC and \$360,000 in Chicago. Boston and Philadelphia's highest averages were in 2013 with annual average medallion values of about \$682,000 and \$469,000.

⁷¹ Using the highest annual average generates the most conservative estimate of the percentage decrease because doing so created the largest denominator and thus generates the smallest percentage decrease.

Uber, medallion values would have continued to rise over time, and thus the estimated decrease in price can logically exceed the city historic average medallion values.

The average decrease in medallion values can be used to calculate the total loss to the taxi industry of each city by multiplying it by the number of medallions in the city. Estimates of these losses range from \$9.58 billion in NYC to \$386.5 million in Philadelphia. Differences in the losses across cities are driven by both differences in the average decreases in medallion values and the number of medallions in each city. NYC has both a large estimated average decrease per medallion and a large number of medallions, which causes its estimated loss to the industry to be greatest. Chicago is estimated to have experienced industry losses of \$2.19 billion, followed by Boston with \$1.27 billion, and Philadelphia with \$836.5 million. An interesting comparison is that of the losses to the taxi industries in the four cities studied here and the gains in consumer surplus estimated by Cohen et al. (2016).

Cohen et al. (2016) estimate gains in consumer surplus for a group of four cities (Chicago, Los Angeles, NYC, and San Francisco) to be \$2.88 billion annually. To compare my estimates of the losses to the taxi industry to the increase in consumer surplus, I multiply the sum of total industry losses by a discount rate of 5 percent to estimate annual losses to the industries in the four cities.⁷² The industry losses associated with the introduction and expansion of Uber in NYC, Chicago, Boston and Philadelphia is an estimated \$6.71 million annually, which represents roughly 23.3 percent of the annual gains to consumers.⁷³ This comparison suggests that the gain to consumers created

⁷² Summation of total industry losses is \$13.43 billion. $\$13.43 \text{ billion} \times 0.05 = \6.71 million .

⁷³ Using alternative discount rates of 3 percent and 7 percent change the annual industry losses to \$4.03 million and \$9.4 million, which represent 13.99 and 32.6 percent of estimated consumer gains.

by the introduction and expansion of Uber substantially outweighs the loss to producers. This, however, is not a perfect comparison of the gains to consumers and losses to producers attributed to Uber. The total gain in consumer surplus for NYC, Chicago, Boston, and Philadelphia is likely different than that of NYC, Chicago, San Francisco, and Los Angeles, which was estimated by Cohen et al. (2016). The gains in consumer surplus for NYC, Chicago, Boston, and Philadelphia are arguably less than the estimated \$2.88 billion annually because the four cities used in the analysis were those with Uber's largest markets. Additionally, the estimated losses in taxi medallion values attributable to just Uber as a rideshare service likely overstated. During the period of this study, Lyft entered each of the four cities. Due to data restrictions, I was unable to control for this in my estimation and because Lyft, too, likely causes medallion values to fall, my estimates of the effect of Uber on medallion values is overstated. The magnitude of this overstatement, however, is likely small as Uber's market share is much larger than Lyft's in each of the four cities studied here. Nonetheless, my estimates suggest that the benefit to consumers is far greater than the loss to producers and it is unlikely that using the estimated consumer surplus gain in NYC, Chicago, Boston, and Philadelphia would reverse this finding.

DEMAND ESTIMATIONS

Data on all bids submitted to auctions provide a unique opportunity to map out demand for taxi medallions. Using both winning and non-winning bids from two auctions—one an auction of independent medallions and the other an auction of corporate medallions—in New York City in 2004, I estimate and graphically display demand functions for corporate and independent taxi medallions in the city during that time period.

Demand for Corporate Medallions

To estimate the demand for corporate medallions in New York City, I analyze auction bids from the April 18, 2004 auction of 87 unrestricted corporate medallions.⁷⁴ I create the demand schedule by ordering the bids from highest to lowest and then assigning them numbers (e.g., 1,2,3...). Each bid represents an individual bidder's willingness to pay for a medallion. Numbering the bids creates the quantity demanded at a certain price. For instance, at the third highest bid amount, quantity demanded is three. Alternatively, this approach identifies the willingness to pay for different quantities of additional medallions. Figures 14 and 15 plot bid amounts against quantity demanded and fitted linear or quadratic values. Plotting the bids against quantity creates a graphical representation of the demand for corporate medallions in NYC.

⁷⁴ Twelve bids were either incomplete or invalid bids and were dropped, resulting in 447 usable observations. All bid amounts were divided by two because corporate medallions are auctioned in sets of two by the TLC.

Figure 14: Corporate demand for medallions with linear fitted values

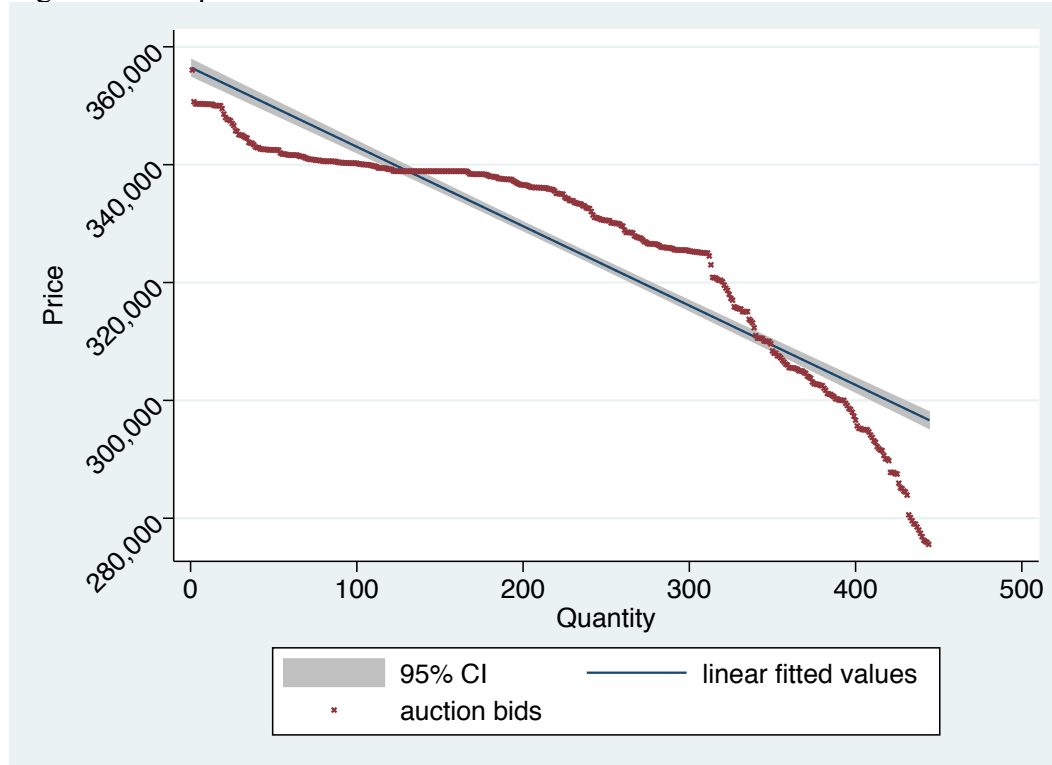


Figure 14 plots auction bids from the April 16, 2004 auction of 87 corporate, unrestricted medallions in NYC and linear fitted values with a 95% confidence interval.

Figure 14 shows the actual bids from the auction and the linear fitted values with a 95 percent confidence interval. The relationship between bid amount and quantity appears to be poorly represented by a linear function. Figure 15 again plots the auction bids but instead fits a quadratic function to the values as opposed to a linear function.

Figure 15: Corporate demand for medallions with quadratic fitted values

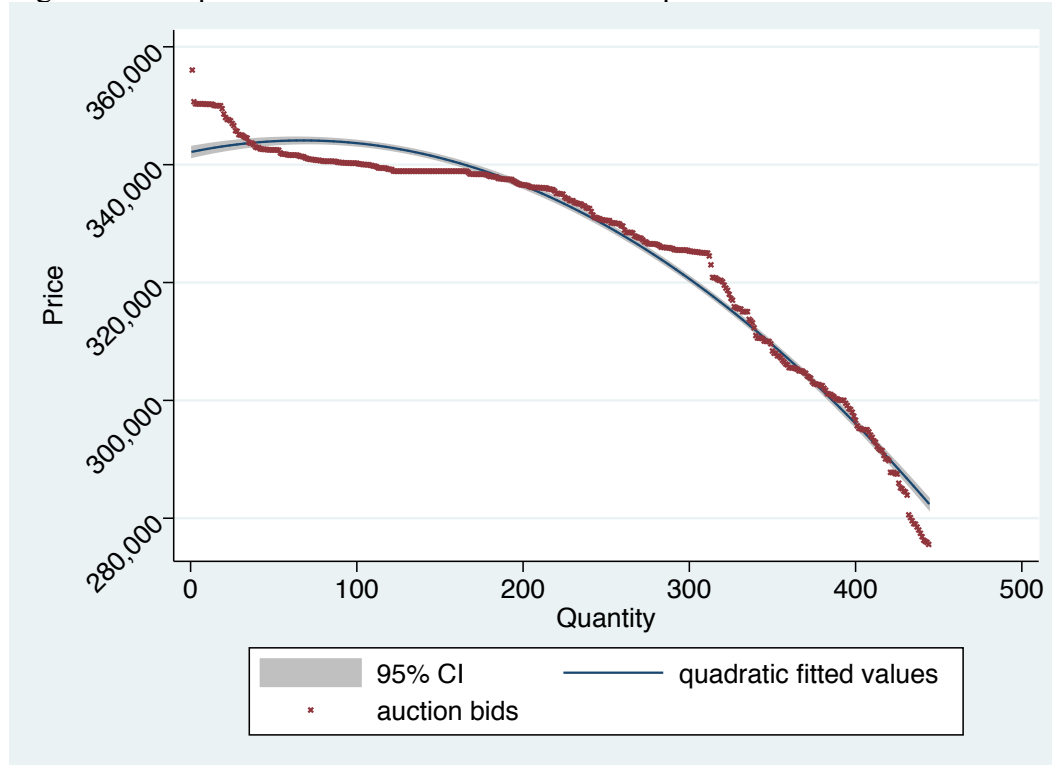


Figure 15 plots auction bids from the April 16, 2004 auction of 87 corporate, unrestricted medallions in NYC and quadratic fitted values with a 95% confidence interval.

The quadratic functional form appears to better describe the nature of the demand for corporate medallions than the linear form. Figures 14 and 15 suggest demand for corporate medallions is downward sloping and increasing with quantity demanded.⁷⁵ The linear and quadratic fitted values were calculated by regressing bid amount on quantity demanded. Results from these regressions are shown in table 9.

⁷⁵ The quadratic fitted values in figure 12 increase until a quantity of 67.4

Table 9: Corporate medallion demand function estimations

Inverse linear demand

function: price = 356,500.20 - 134.71(quantity)

Inverse quadratic demand

function: price = 342,129.20 + 58.62(quantity) - 0.435(quantity²)

Note: all coefficients are significant at the 1% level.

Under a quadratic functional form, the fitted values are closer to the observed values—i.e., the actual auction bids—than under the linear functional form. Because of this, estimates of the demand function for corporate medallions with a quadratic functional form are preferred. The estimated demand function assuming a quadratic functional form estimates the vertical intercept (the highest willingness to pay for a medallion) to be about \$356,500. A peculiar aspect of the demand curve estimated under the assumption of a quadratic relationship is that the function is increasing until a quantity of about 67 medallions. This upward sloping portion of the estimated demand curve is odd but only refers to the initial part of the function and is a direct implication of the functional form assigned to the demand curve. While the quadratic estimated demand curve does not perfectly represent the actual bid values when quantity demanded is low, the fitted values and actual bids are markedly similar after the quantity demanded reaches roughly 175 medallions.

Demand for Independent Medallions

The demand for independent medallions is estimated by the same process as the demand for corporate medallions. Data on winning and non-winning bids from the October 18, 2004 auction of 116 unrestricted independent medallions are sorted from highest to lowest and assigned quantities.⁷⁶ Figure 16 plots the individual bids and fitted linear values with 95 percent confidence intervals. The linear fitted values are quite similar to the actual bid values for most of the bids, but the predicted values vary from the actual values in the tails of the bid amounts. By using a quadratic functional form, I allow for more flexibility in the shape of the fitted values.

Figure 16: Independent demand for medallions with linear fitted values

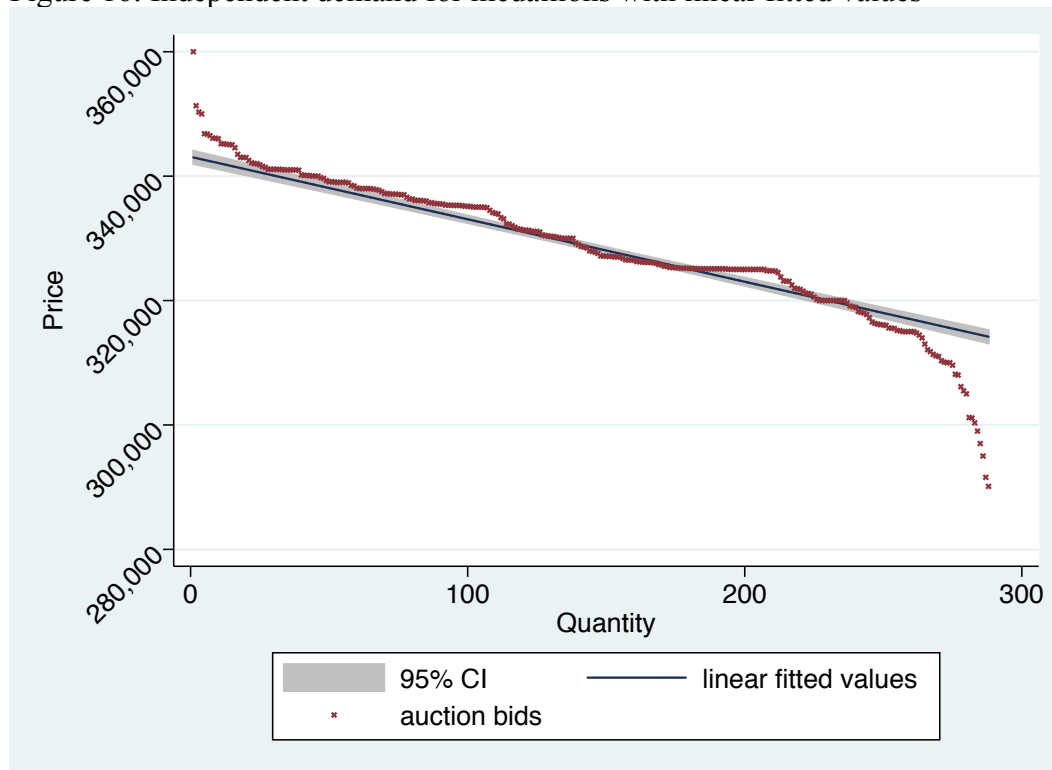


Figure 16 plots auction bids from the October 18, 2004 auction of 116 independent, unrestricted medallions in NYC and linear fitted values with a 95% confidence interval.

⁷⁶ One bid received was invalid and dropped, resulting in 288 usable bids.

Figure 17 plots the bid amounts and quadratic fitted values with 95 percent confidence intervals. The quadratic functional form appears to be a better fit than the linear form for the demand of independent medallions. While the majority of the bids are predicted quite well under both the linear and quadratic models, the quadratic fitted values are closer to the actual values in the tails of the bids data than those of the linear fitted values.

Figure 17: Independent demand for medallions with quadratic fitted values

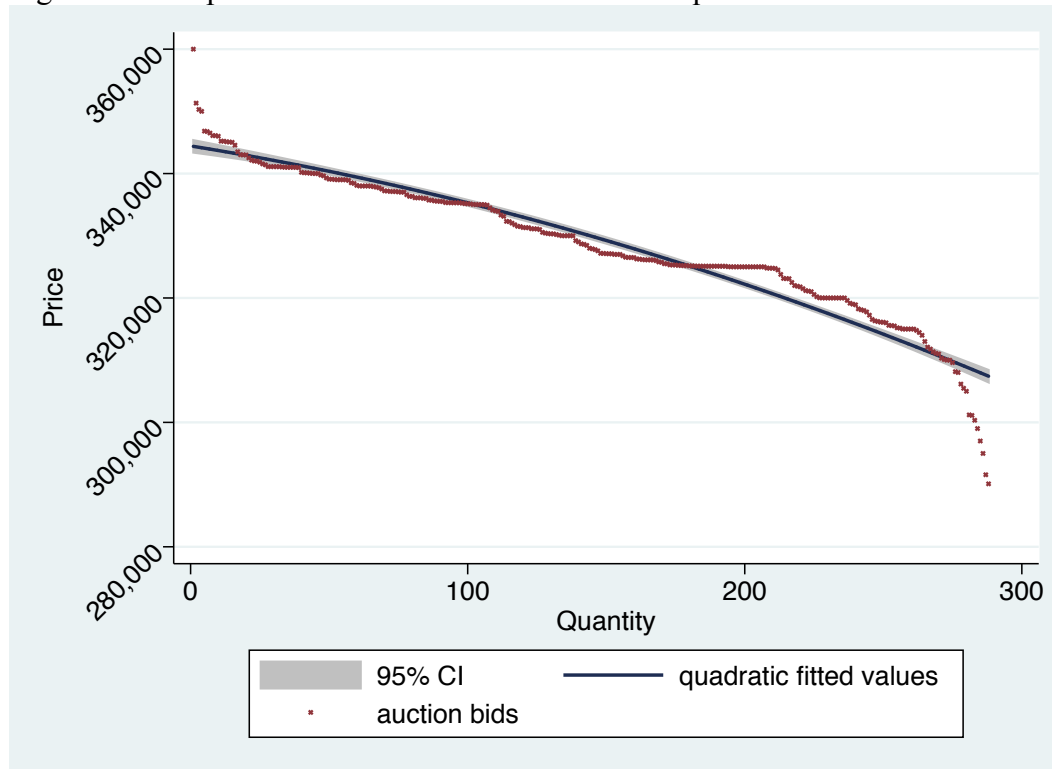


Figure 17 plots auction bids from the October 18, 2004 auction of 126 independent, unrestricted medallions in NYC and quadratic fitted values with a 95% confidence interval.

The inverse demand functions estimated under both the linear and quadratic models are listed in table 10. Under both models, demand is estimated to be downward sloping with a vertical intercept between roughly \$344,000 and \$347,000. As discussed

above, the quadratic model better predicts actual bids in the tails of the data, but the two models are quite similar in representing the actual bid values for the majority of the bids.

Table 10: Corporate medallion demand function estimations

<i>Inverse linear demand function:</i>	$\text{price} = 347,196.60 - 128.72(\text{quantity})$
<i>Inverse quadratic demand function:</i>	$\text{price} = 344,441.90 - 71.73 (\text{quantity}) - 0.197(\text{quantity}^2)$

Note: all coefficients are significant at the 1% level.

ROBUSTNESS CHECK

To assess the strength of the results, I conduct a placebo test where I implement the number of Uber drivers in January 2007 instead of June 2012.⁷⁷ This allows me to examine the robustness of my results by testing whether the number of Uber drivers is simply picking up the trend in medallion prices over time. Table 11 shows results from regressions using the placebo variable for the number of drivers that begins in January 2007.

Table 11: Falsification Test

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers (placebo)	-4.633** (1.457)	1.976 (1.832)	0.811 (1.312)	0.0191 (0.246)	-0.261 (0.488)	-0.287 (0.464)
Restricted medallion	217,957*** (42,296)	-60,149 (76,227)	-129,298 (84,590)	-120,497** (39,579)	-121,703** (42,904)	-121,205** (41,824)
Independent medallion	106,439 (153,090)	32,554 (102,507)	30,521 (93,500)	-93,334*** (4,623)	-92,304*** (5,449)	-92,203*** (5,318)
Auction	-152,488*** (29,408)	108,962* (49,997)	208,547** (78,105)	128,505** (54,546)	129,243* (58,943)	127,012* (57,141)
Population	0.0555* (0.0277)	0.0585** (0.0170)	0.0595** (0.0155)	0.413*** (0.0388)	0.0862 (0.259)	0.000331 (0.273)
Unemployment rate	24,253 (17,324)	-24,072* (12,237)	-31,248* (13,552)	-1,417 (956.4)	3,349 (2,277)	4,347* (2,627)
Gasoline price per gallon	-4,311 (23,489)	-38,861* (17,583)	-52,780* (24,627)	9,234 (5,813)	10,531* (4987)	11,345** (4,390)
Real interest rate	-21,752* (12,643)	-4,765 (4,930)	-4,924 (4,244)	6,723* (3,791)	5,290* (2,654)	5,024* (2,626)
Linear monthly time trend		5,619** (1,088)	46,907** (13,726)	20,397 (9,857)	4,305*** (312.9)	
Quadratic monthly time trend			-33.99** (10.67)	-13.72 (7.886)		3.514*** (0.266)
City specific monthly linear time trend	No	No	No	No	Yes	No
City specific monthly quadratic time trend	No	No	No	No	No	Yes
City fixed effects	No	No	No	Yes	Yes	Yes
N	7,107	7,107	7,107	7,107	7,107	7,107
R ²	0.545	0.752	0.760	0.839	0.839	0.839

Notes: Robust standard errors clustered at the city level in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator, Observations from Philadelphia's 2015 auctions are dropped.

⁷⁷ January 2007 is chosen because the data on medallion values begins before or at this time for all cities except Boston and the time span of the number of Uber drivers ends before the actual introduction of Uber and thus the placebo number of Uber drivers does not overlap the actual number of drivers.

The statistically insignificant coefficient estimates for the number of Uber drivers variable in all but the first model suggests that the variable is not picking up trends in the price of medallion variables that are not controlled for by the other explanatory variables in the model. If the number of Uber drivers variable was picking up the effects of some omitted variable that affects the values of taxi medallions, the coefficient estimate would be statistically significant and consistent in sign across the different models. Lack of statistically significant coefficient estimates, or even estimates of large magnitude, suggests that the number of Uber drivers variable is indeed picking up the effect of the changes in the number of Uber drivers on medallion values.

CONCLUSION

The results of this paper suggest that the entrance and expansion of Uber as a main competitor in the transportation sector has notably impacted the taxi industry by substantially decreasing the value of taxi medallions. Findings indicate that in the four cities analyzed, Uber has created significant losses to the taxi industries of each city, ranging from \$387 million in Philadelphia to \$9.6 billion in NYC. Losses per medallion range from nearly \$718,000 in NYC to \$240,000 in Philadelphia, which represent sizable decreases in price relative to even the highest medallion values recorded in each city. The negative effect of increases in the number of Uber drivers on medallion values is estimated to be different across cities and across the number of Uber drivers, resulting in different estimated aggregate losses to medallions in the four cities. When comparing the total annualized industry losses of NYC, Chicago, Boston, and Philadelphia to the annual gain in consumer surplus in Uber's four largest markets, losses to producers—as measured by the decrease in medallion values—are estimated to be roughly a quarter of the size of the annual gains to consumers.

Results also suggest that medallion values are impacted by economic conditions such as the unemployment rate, input prices like the price of gasoline, and city demographics (i.e., population). Medallion characteristics such as whether the medallion is designated for use in a wheelchair accessible or alternative fuel taxi are also found to impact medallion values. The sale mechanism—person-to-person transfers of medallions vs. auctions of medallions—is shown to result in a difference in price. This difference is

likely driven by differences in the number of potential buyers associated with the two sale mechanisms.

This work estimates the substantial negative impact of the introduction and expansion of Uber on the value of taxi medallions but Uber's effect on other areas of the taxi industry may also be of interest. Uber's effect on waiting times, distances traveled, and taxi maintenance are all interesting questions that have yet to be analyzed. The effect measured in table 8 is the aggregate effect of Uber on medallion values in December 2015 in each of the cities in this study.⁷⁸ The decrease in medallion values may become larger over time—assuming that Uber and other ride sharing companies continue to grow. In the absence of regulation on ridesharing companies, the negative effect of Uber and other ridesharing companies on medallion values will likely persist until medallions are valueless. The theoretical and empirical analysis in this paper may provide insights into the effect of Airbnbs and breweries on the hotel industry and restaurants and bars subject to liquor license requirements. Possible extensions of this work include analyzing how the effect of additional Uber drivers on medallion values has changed since December 2015, examining the determinants of the number of medallion transfers in a given period, estimating the effect of the introduction and expansion of Uber on medallion stock transfers and how it compares to its effect on asset transfers, and if the early entry of Uber to certain cities affects medallion values in cities where Uber enters the market later.

⁷⁸ See table 8 for specific values used in estimation.

REFERENCES CITED

Banovetz III, James Michael Banovetz. "An economic analysis of the determinants of Montana alcohol retail license prices." PhD diss., Montana State University-Bozeman, College of Agriculture, 2014.

Beesley, Michael E. "Regulation of taxis." *The Economic Journal* 83, no. 329 (1973): 150-172.

Beesley, Michael E., and Steven Glaister. "Information for regulating: the case of taxis." *The Economic Journal* 93, no. 371 (1983): 594-615.

Berdik, Chris. "Fare Game." *The Boston Globe*, September 2004.

Boston Cab Dispatch, Inc. and EJT Management v. Uber Technology, Mass Civil Action No. 13-10769-NMG. United States District Court: District of Massachusetts. 2014.

Boston Police Department. "Rule 403 Rule 403 Hackney Carriage Rules Hackney Carriage Rules and Flat Rate Handbook Flat Rate Handbook." *Boston Police Department*. August 29, 2008.

Boston Police Department. "Taxi Rates." *BPD News*.

Brown, A. Blake, Randal R. Rucker, and Walter N. Thurman. "The End of the Federal Tobacco Program: Economic Impacts of the Deregulation of US Tobacco Production." *Review of Agricultural Economics* (2007): 635-655.

Cairns, Robert D., and Catherine Liston-Heyes. "Competition and regulation in the taxi industry." *Journal of Public Economics* 59, no. 1 (1996): 1-15.

Carroll, Sidney L., and Robert J. Gaston. "Occupational restrictions and the quality of service received: some evidence." *Southern Economic Journal* (1981): 959-976.

City of Chicago. "Passenger Information." *City of Chicago Business Affairs Consumer Protection*. January 1, 2016.

Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe. "Using Big Data to Estimate Consumer Surplus: The Case of Uber." No. w 22627. *National Bureau of Economic Research*, 2016.

Conway, Madeline, and John Reynolds. "The Brief: Lawmakers asked to weigh in on ride-hailing regulations." *The Texas Tribune*, June 9, 2016.

Cramer, Judd and Alan B. Krueger. "Disruptive Change in the Taxi Business: The Case of Uber." *NBER Working Paper*, 22083, 2016.

De Vany, Arthur S. "Capacity utilization under alternative regulatory restraints: an analysis of taxi markets." *Journal of Political Economy* 83, no. 1 (1975): 83-94.

Dills, Angela K. and Mulholland, Sean E., Ride-Sharing, Fatal Crashes, and Crime (February 13, 2017). Available at SSRN: <https://ssrn.com/abstract=2783797>

Engquist, Erik. "Judge Rules on Taxi Industry Lawsuit: Compete with Uber or Die." *Crain's New York Business*, September 9, 2015.

Federman, Maya N., David E. Harrington, and Kathy J. Krynski. "The impact of state licensing regulations on low-skilled immigrants: The case of Vietnamese manicurists." *American Economic Review* 96, no. 2 (2006): 237-241.

Fichtenbaum, Rachel. "Wheelchair-Accessible Taxicabs." *Executive Office of Health and Human Services' Human Transportation Offices, Massachusetts*, October 2013.

Pautler, Paul A., and Mark W. Frankena. "An Economic Analysis of Taxicab Regulation." *Bureau of Economics Staff Report* (1984).

Gallick, Edward C., and David E. Sisk. "A reconsideration of taxi regulation." *Journal of Law, Economics, and Organization*. 3, no. 1 (1987): 117.

Greenwood, Brad N. and Wattal, Sunil. "Show Me the Way to Go Home: An Empirical Investigation of Ride Sharing and Alcohol Related Motor Vehicle Homicide." *Fox School of Business Research Paper No. 15-054* January 2015.

Hall, Jonathan V., and Alan B. Krueger. "An analysis of the labor market for Uber's driver-partners in the United States." No. w22843. *National Bureau of Economic Research*, 2016.

Kitch, Edmund W., Marc Isaacson, and Daniel Kasper. "The regulation of taxicabs in Chicago." *Journal of Law and Economics* 14, no. 2 (1971): 285-350.

Leffler, Keith B., and Randal R. Rucker. "Transactions Costs and the Efficient Organization of Production: A Study of Timber-Harvesting Contracts." *Journal of Political Economy* 99, no. 5 (1991): 1060-1087.

Lei, Lei, Bradley Rickard, Joseph Balagtas, and Barry Krissoff. "A closer look at the role of the fruit and vegetable planting restriction provision on land use in the United States." In Paper presentation, Agricultural and Applied Economics Association Joint Annual Meeting. 2011.

Municipal Code of Chicago. Chapter 9-112. 2013.

Nelson/Nygaard Consulting Associates. "Taxi Fare Rate Study." *City of Chicago, Business Affairs and Consumer Protection*. August 2014.

Nicholson, Chris. "Study: Uber Pulls Ahead of Lyft in Riders and Revenue With 12x Lead in U.S." *FutureAdvisor Blog* (web log), September 11, 2014.

Officer, Ari J. "What Caused the Big Slide in Oil Prices." *Time*, November 14, 2008.

Philadelphia Parking Authority. "Medallion Renewal Form." *Philadelphia Parking Authority*. 2017.

Philadelphia Parking Authority, "Taxicab and Limousine Regulations." *Philadelphia Parking Authority*. 2011.

Philadelphia Parking Authority. "Taxicab Tariff." *Philadelphia Parking Authority*. 2014.

Pennsylvania Code Title 52, Public Utilities, Chapter 30.

Posner, Richard A. "Theories of Economic Regulation." *Bell Journal of Economics and Management Science*, 53 no. 2 (1974): 335-358.

Rahel, Steven, "Economics of the Taxi Industry: An Uber Shake-up." *Honors Theses AY 15/16*. Paper 28. 2016.

Roistacher, Elizabeth A. and Lawrence J. White, "The Pricing of Taxicab Medallions in New York City." *Mayor's Committee on Taxi Regulatory Issues, Consultant and Staff Studies Volume*. March 1982.

Rucker, Randal R., and Dominic Parker. "Collaborative Research: The Value of Government Created Assets: Taxi Medallions and Liquor Licenses in Evolving Markets." Proposal to the National Science Foundation. 2017.

Rucker, Randal R., Walter N. Thurman. "The Economic Effects of Supply Controls: The Simple Analytics of the US Peanut Program. *Journal of Law & Economics*, 33 no. 2 (1990): 483-515.

Rucker, Randal R., Walter N. Thurman, and Daniel A. Sumner. "Restricting the market for quota: an analysis of tobacco production rights with corroboration from congressional testimony." *Journal of Political Economy*, 103 no.1 (1995): 142-515

Russo and DeBlasis, Safety concerns remain for Uber, Lyft ride sharing." *Maryland Reporter*, May 15, 2016.

Sanchez, Karizza. "How Safe is Uber in New York City?" *Complex*, May 20, 2016.

Schaller, Bruce. "Entry controls in taxi regulation: Implications of US and Canadian experience for taxi regulation and deregulation." *Transport Policy*, 14 no. 6 (2007): 490-506.

Schneider, Henry. "Moral hazard in leasing contracts; Evidence from the New York City taxi industry." *Journal of Law and Economics*. 53, no. 4 (2010): 783-805.

Shreiber, Chanoch. "The Economic Reasons for Price and Entry Regulation of Taxicabs." *Journal of Transport Economics and Policy* (1975): 268-279.

Sumner, Daniel A., and Christopher A. Wolf. "Quotas without supply control: effects of dairy quota policy in California." *American Journal of Agricultural Economics* 78, no. 2 (1996): 354-366.

"Taxi owners, lenders sue New York City over Uber." *CNBC News*, November 17, 2015.

TLC. Taxicab Rate of Fare. *Taxi and Limousine Commission of New York City*, 2017.

TLC. Rules and Local Laws, Chapter 58. *Taxi and Limousine Commission of New York City*. 2017.

TLC. Rules and Local Laws, Chapter 80. *Taxi and Limousine Commission of New York City*. 2017.

Uber. "License Requirements, New York City." *Uber Technologies*, n.d.

Uber. "Driver Requirements." *Uber Technologies*, 2017.

Uber. "Our Story." *Uber Technologies*, 2017.

Uber. "Ride." *Uber Technologies*, 2017.

Uber. "Help: What is surge?" *Uber Technologies*, 2016.

Uber. "Uber on the Streets of Philadelphia." *Uber Technologies*, June 4, 2012.

Uber. "Chicago – Uber's biggest Launch to date?" *Uber Technologies*, September 22, 2011.

Uber. "Uber NYC has launched." *Uber Technologies*, May 3, 2011.

Uber. "Uber Sighting in Boston?!!!" *Uber Technologies*, October 5, 2011.

U.S. Bureau of Labor Statistics. "Local Area Unemployment Statistics." *U.S. Bureau of Labor Statistics*. 2016.

U.S. Census Bureau. "Population." *U.S. Census Bureau*. 2016.

U.S. Energy Information Administration. "Weekly Retail Gasoline and Diesel Prices." *U.S. Energy Information Administration*. 2016.

Van Gelder, Lawrence. "Medallion Limits Stem From the 30's." *The New York Times*. May 10, 1996.

Wooldridge, Jeffrey M. "Introductory Econometrics: A Modern Approach." *Nelson Education*, 5th Edition, 2012.

Yi, Kei-Mu and Jing Zhang. "Real Interest Rates over the Long Run." *Federal Reserve Bank of Minneapolis, Economic Policy Paper 16-10*, September 2016.

"2014 Taxicab Fact Book." *Taxi and Limousine Commission of New York City*. 2014.

APPENDICES

APPENDIX A

NYC REGRESSION RESULTS EXCLUDING JANUARY 2015 OBSERVATIONS

The oddly low average medallion transfer prices in NYC in January 2015—shown in figure 6—raise concerns that the sharp decrease in average medallion value might driving the results for NYC. By estimating the model used to analyze the effect of the number of Uber drivers on medallion values in NYC again without the low medallion transfer prices from January 2015, I determine that the low values do not appear to be driving the results. Table 12 shows results from the NYC model when the unusually low medallion transfer values from January 2015 are dropped. Coefficient estimates remain very similar to those shown in table 3, which shows the estimation results when including the low values from January 2015.

Coefficient estimates for the number of Uber drivers remain negative and statistically significant. Estimates for the explanatory variables are also very similar to those estimated with the inclusion of the low medallion values from January 2015. The consistency in the coefficient estimates across the two estimations suggests that the low medallion transfer values in January 2015 are not causing of the results.

Table 12: Effect of Uber on taxi medallion values: NYC (low observations omitted)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-13.82*** (2.75)	-22.17*** (2.69)	-32.37*** (3.16)	29.41*** (7.16)	14.76** (6.98)	0.488 (8.29)
Number of Uber drivers ²				-0.00165*** -0.000257	-0.00140*** -0.000249	-0.00111*** -0.000264
Wheelchair accessible medallion	-5,095 (16375)	-157,921*** (16241)	-143,917*** (16377)	-17,202 (16040)	-162,201*** (16641)	-152,170*** (16705)
Alternative fuel medallion	-53,482*** (16375)	-194,959*** (16241)	-181,401*** (16377)	-47,596*** (16040)	-184,447*** (16641)	-177,757*** (16705)
Independent medallion	-106,304*** -5,753	-83,327*** -5,818	-82,888*** -5,750	-106,287*** -5,743	-84,210*** -5,811	-83,742*** -5,772
Auction	-11,303 (11037)	199,618*** (15775)	166,339*** (16248)	-33,644*** (11738)	172,460*** (16748)	156,316*** (16704)
Population	1.356*** (0.070)	0.146* (0.102)	-0.988*** (0.195)	0.934*** (0.092)	-0.164* (0.115)	-0.841*** (0.194)
Unemployment rate	-799.4 (4103)	-23,291*** (4045)	-14,491*** (4067)	13,040*** (4397)	-10,694*** (4320)	-7,541** (4277)
Gasoline price per gallon	14,925* (9759)	-50,810*** (9110)	-49,691*** (9146)	27,328*** (9745)	-37,739*** (9033)	-39,702*** (9109)
Real interest rate	20,486*** (2939)	9,193*** (2574)	3443 (2742)	14,298*** (3115)	4,395* (2784)	1627 (2820)
Linear monthly time trend		7,663*** (418.5)	-69,965*** (11641)		7,363*** (414.8)	-43,288*** (12586)
Quadratic monthly time trend			69.49*** (10.44)			45.40*** (11.30)
N	2,818	2,818	2,818	2,818	2,818	2,818
R ²	0.635	0.675	0.681	0.647	0.683	0.686

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator, Observations from January 2015 are dropped

APPENDIX B

NYC MONTHLY AND ANNUAL REGRESSION RESULTS

The abundance of data in New York City allows for two additional analyses of the effect of Uber's presence on taxi medallion values. The first additional analysis utilizes monthly average transfer price data from NYC over the time span of 1992–2015. Using these data, I estimate the following OLS model:

$$\begin{aligned}
 (4) \quad & Avg_Trans_Price_{it} \\
 &= \beta_0 + \beta_1 Num_Drivers_t + \beta_2 Num_Drivers_t^2 + \beta_3 Independent_{it} \\
 &+ X_t \lambda + \phi * t + \theta * t^2 + \varepsilon_{it}
 \end{aligned}$$

$Avg_Trans_Price_t$ is the monthly average transfer price in month t for medallion type i . $Num_Drivers_t$ and $Num_Drivers_t^2$ are the number of Uber drivers at time t and the number of Uber drivers squared at time t . $Independent_{it}$ is an indicator variable equaling one when the monthly average is an average of independent medallions and equaling zero when the monthly average is of corporate medallions. X_t is a vector of control variables at time t including population, the unemployment rate, gasoline prices, and the real interest rate. $\phi * t$ and $\theta * t^2$ represent linear and quadratic time trends. ε_{it} is the error term. Predictions for the variables in the model are equivalent to those of the prior estimations.

Table 13 presents the results from the monthly estimations in NYC. The number of Uber drivers is estimated to have a negative impact on medallion values under all six specifications.⁷⁹ Coefficient estimates for the number of Uber drivers are statistically significant under specifications 1, 2, and 3, which assume a linear relationship between medallion values and the number of Uber drivers. When comparing the estimates from specifications 1-3 in the monthly model to the same

⁷⁹ Under specification 4, the effect becomes negative after 5,546 Uber drivers enter the market.

specifications under the model using individual transaction data (results shown in table 3), the coefficient estimates are smaller in magnitude using the monthly data—equaling roughly half the size of the estimates from the model using individual transaction data. While the coefficient estimates under specifications 4-6 are largely statistically insignificant, the estimates are of the expected sign. The coefficient estimates for the control variables are statistically insignificant or estimated to be of the opposite than predicted sign.⁸⁰ This might be due to the low number of observations of 557. Nonetheless, the coefficient estimates of the effect of Uber's presence on the value of taxi medallions is estimated to be negative and statistically significant across specifications 1-4. The estimates are smaller in magnitude than those of the model using individual transaction data, but are still meaningful and economically significant. Using the coefficient estimate from specification 2, the total aggregate loss to the taxi industry is roughly \$3.74 billion.⁸¹

The second additional analysis the NYC data allow me to conduct is an annual analysis. Using annual average medallion transfer price data by medallion type from 1947-2015, I am able to look at a longer time horizon. To do so, I estimate the following OLS model:

$$\begin{aligned}
 (5) \quad & Avg_Trans_Price_{it} \\
 & = \beta_0 + \beta_1 Num_Drivers_t + \beta_2 Num_Drivers_t^2 + \beta_3 Independent_{it} \\
 & + + X_t \lambda + \phi * t + \theta * t^2 + \varepsilon_{it}
 \end{aligned}$$

⁸⁰ With the exception of the coefficient estimate population, which is statistically significant under some of the specifications and is of the predicted sign.

⁸¹ Calculation: $9.897 * 28,326 * 13,333 = 3,737,805,512.53$

The model is analogous to equation (4) that was used in the monthly estimation, except the unit of time is now years instead of months. $Avg_Trans_Price_t$ is the annual average transfer price in year t for medallion type i . $Num_Drivers_t$ and $Num_Drivers_t^2$ are the annual average number of Uber drivers at time t and the annual average number of Uber drivers squared at time t . $Independent_{it}$ is an indicator variable equaling one when the annual average is an average of independent medallions and equaling zero when the annual average is of corporate medallions. X_t is a vector of control variables at time t including the unemployment rate, gasoline prices, and the real interest rate. $\phi * t$ and $\theta * t^2$ represent linear and quadratic annual time trends. ε_{it} is the error term. Predictions are again the same as discussed prior.

Table 14 presents results from the annual estimations. Coefficient estimates for the number of Uber drivers suggest a negative and statistically significant relationship between the number of Uber drivers and medallion values.⁸² Coefficient estimates on the other explanatory variables are statistically insignificant—with the exception of gasoline prices under some specifications. The lack of precision in annual estimations could be again due to the low number of observations of 110. Nonetheless, the effect of Uber is consistent across city specific, pooled, monthly, and annual estimates suggesting the effect is robust.

⁸² This estimated effect is initially positive under specifications 4-6 but becomes negative after a certain threshold in the number of Uber drivers is passed.

Table 13: Effect of Uber on taxi medallion values: NYC Monthly Estimations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	-4.848*** (2.017)	-9.897*** (2.495)	-12.70*** (4.836)	5.287 (7.091)	-2.236 (7.409)	-4.036 (10.83)
Number of Uber drivers ²				-0.000476* (0.000320)	-0.000351 (0.000319)	-0.000316 (0.000353)
Independent medallion	-34,118** (16,385)	-34,825** (16,233)	-34,704** (16,242)	-34,067** (16,367)	-34,760** (16,230)	-34,721** (16,245)
Population	0.146*** (0.0376)	-0.0418 (0.0669)	-0.0351 (0.0677)	0.142*** (0.0376)	-0.0373 (0.0670)	-0.0352 (0.0677)
Unemployment rate	17,000*** (6,205)	7,671 (6,739)	3,342 (9,300)	15,627*** (6,266)	7,035 (6,762)	5,479 (9,604)
Gasoline price per gallon	34,865** (16,985)	-10,705 (21,568)	-23,424 (28,635)	30,653** (17,200)	-11,978 (21,595)	-16,606 (29,638)
Real interest rate	15,944** (6,839)	8,774 (7,100)	8,162 (7,161)	15,204** (6,849)	8,516 (7,102)	8,313 (7,164)
Linear monthly time trend		1,359*** (402.3)	-850.3 (3,294)		1,304*** (405.3)	484.0 (3,617)
Quadratic monthly time trend			2.200 (3.256)			0.822 (3.603)
N	557	557	557	557	557	557
R ²	0.095	0.113	0.114	0.099	0.115	0.116

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator

Table 14: Effect of Uber on taxi medallion values: NYC Annual Estimations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Number of Uber drivers	1.318 (2.781)	-6.144** (2.665)	-11.87*** (2.543)	33.99*** (9.657)	22.81** (9.241)	13.17 (9.860)
Number of Uber drivers ²				-0.00163*** (0.000438)	-0.00144*** (0.000421)	-0.00123*** (0.000447)
Independent medallion	-9,813 (22,044)	-6,475 (14,560)	-6,353 (12,860)	-9,278 (21,640)	-6,029 (14,018)	-5,977 (12,398)
Unemployment rate	-9,793 (8,215)	-10,631** (4,848)	-447.8 (4,044)	-8,235 (8,290)	-9,245* (4,747)	277.2 (4,029)
Gasoline price per gallon	88,439*** (16,889)	19,287 (12,433)	-25,814** (11,472)	73,692*** (17,111)	6,796 (11,297)	-34,463*** (10,623)
Real interest rate	-8,690 (5,429)	-3,272 (3,562)	4,285 (2,961)	-7,610 (5,452)	-2,360 (3,567)	4,723 (2,975)
Linear yearly time trend		6,314*** (493.5)	-829,718*** (100,139)		6,264*** (489.7)	-791,908*** (108,618)
Quadratic yearly time trend			210.7*** (25.22)			201.1*** (27.36)
N	110	110	110	110	110	110
R ²	0.227	0.669	0.745	0.261	0.696	0.765

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using an annual GDP deflator

APPENDIX C

ALTERNATIVE MODEL FOR POOLED SAMPLE

Table 15 shows results from pooled city estimations with the addition of a quadratic term on the number of Uber drivers variable. Coefficient estimates for the number of Uber drivers and the number of Uber drivers squared are generally statistically insignificant across specifications 1-6. This is likely because the relationship between the number of Uber drivers and medallion values varies across cities. Estimating this relationship with a pooled the sample generates the same coefficient estimate for the relationship between medallion values and the number of Uber drivers across all the cities, which is likely the cause of the statistical insignificance. Specification 7 adds interaction terms by city for the number of Uber drivers and the number of Uber drivers squared.

Under this specification, the coefficient estimates of the interaction terms for both the number of Uber drivers and the number of Uber drivers squared are jointly significant at the 1 percent level. The significance of the interaction terms suggests that the effect of the introduction and expansion of Uber differs across cities in magnitude and across changes in the number of Uber drivers over time. Under this specification, the negative impact of additional Uber drivers on medallion values begins immediately in Chicago, Boston, and Philadelphia, while the negative effect in NYC only occurs after roughly 2,000 drivers enter the market.⁸³ In NYC, Boston, and Philadelphia, the effect of additional Uber drivers on medallion values increases with magnitude—i.e., becomes more negative—as the number of Uber drivers increases.

Alternatively, in Chicago, the effect decreases in magnitude—becomes less negative—as the number of Uber drivers increases. The effect of additional Uber drivers

⁸³ The impact on medallion values of additional Uber drivers becomes negative once the number of drivers in NYC reaches approximately 2,078.

in Chicago is zero when there are roughly 30,000 drivers in the city. Results under specification 7 suggest that the addition of a quadratic term on the number of Uber drivers is appropriate to include if the effect is allowed to vary across cities.

Table 15: Effect of Uber on taxi medallion values - Pooled sample with alternate specification for the number of Uber drivers

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of Uber drivers	71.70** (17.74)	-18.43 (14.88)	-9.951 (16.04)	-1.866 (13.66)	-1.87 (13.15)	-2.998 (12.72)	5.07 (2.653)
Chicago X Number of Uber drivers							-35.83*** (0.975)
Boston X Number of Uber drivers							-24.36** (4.969)
Philadelphia X Number of Uber drivers							-44.25* (15.38)
Number of Uber drivers ²	-0.00283** (0.00078)	-0.000213 (0.00063)	-0.000442 (0.00069)	-0.000595 (0.00058)	-0.000609 (0.00059)	-0.00059 (0.00058)	-0.00122*** (0.00007)
Chicago X Number of Uber drivers ²							0.00174*** (0.000015)
Boston X Number of Uber drivers ²							-0.00113** (0.00024)
Philadelphia X Number of Uber drivers ²							0.000774 (0.0017)
Wheelchair accessible medallion	153,625* (71214)	-9,641 (114076)	-61,472 (118121)	-91,792 (49287)	-107,637* (52649)	-109,430* (52223)	-120,123** (27441)
Alternative fuel medallion	-9,386 (32760)	-132,100** (36474)	-173,240** (48964)	-136,433** (38105)	-153,592** (41488)	-155,797** (40875)	-155,306*** (25170)
Independent medallion	80,250 (146168)	26,400 (98021)	26,133 (92692)	-92,788*** (3778)	-90,302*** (5224)	-89,836*** (5206)	-88,517*** (4453)
Auction	-101,995* (45358)	113,371* (48176)	174,691** (66464)	107,432* (46492)	130,106** (50458)	131,983** (49658)	111,133** (40455)
Population	0.0537* (0.024)	0.0602** (0.015)	0.0603** (0.014)	0.435*** (0.081)	0.142 (0.290)	0.0337 (0.301)	-0.871*** (0.129)
Unemployment rate	14,199 (11302)	-32,733* (14972)	-35,881** (15204)	-6,687* (2940)	-5,312** (1381)	-4,909** (1396)	-1,200 (1584)
Gasoline price per gallon	12,563 (22714)	-69,657* (32592)	-70,907* (32929)	-5,589 (7382)	-6,696 (7642)	-7,204 (7927)	-13,664 (10028)
Real interest rate	-15,834 (10710)	-5,589 (3821)	-5,741 (3585)	5,141* (2894)	3,712** (1320)	3,284** (1199)	-969 (744.5)
Linear monthly time trend	No	Yes	Yes	No	No	No	No
Quadratic monthly time trend	No	No	Yes	Yes	No	No	No
City specific monthly linear time trend	No	No	No	No	Yes	No	Yes
City specific monthly quadratic time trend	No	No	No	No	No	Yes	Yes
City fixed effects	No	No	No	Yes	Yes	Yes	Yes
N	7,107	7,107	7,107	7,107	7,107	7,107	7,107
R-squared	0.66	0.774	0.777	0.848	0.849	0.85	0.856

Notes: Robust standard errors clustered at the city level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Prices are in 2016 dollars using a quarterly GDP deflator, Observations from Philadelphia's 2015 auctions are dropped.

APPENDIX D

ERRORS PLOTTED AGAINST EXPLANATORY VARIABLES

Figure 18: Residuals Against Population

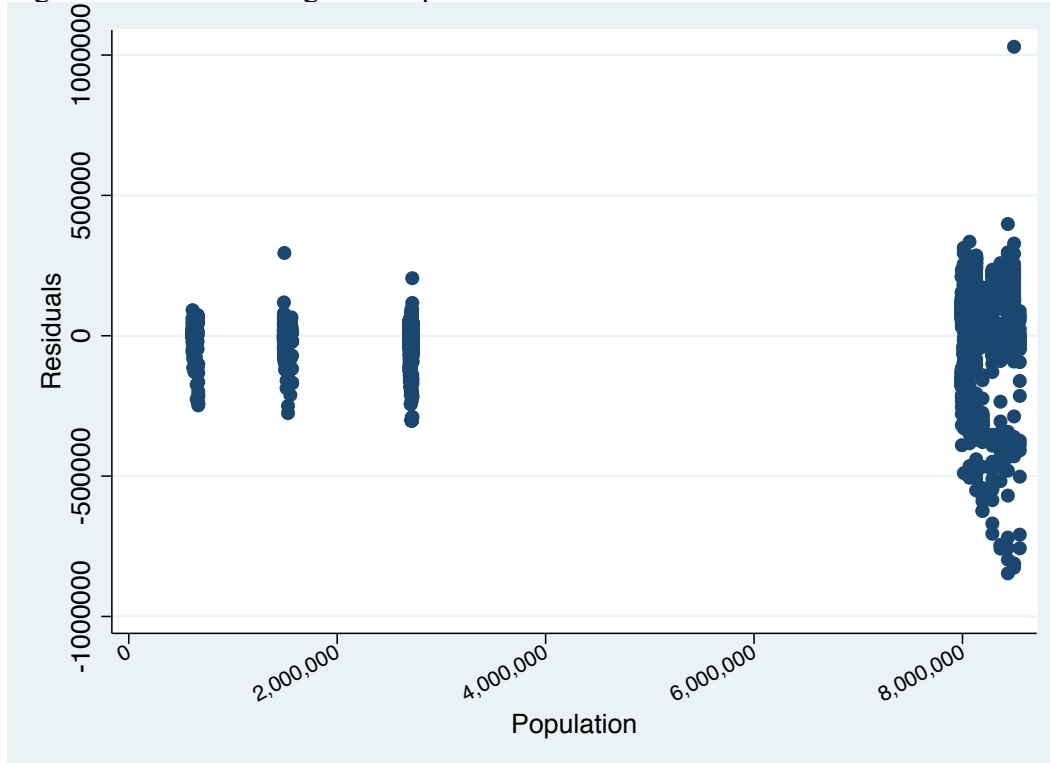


Figure 19: Residuals by City

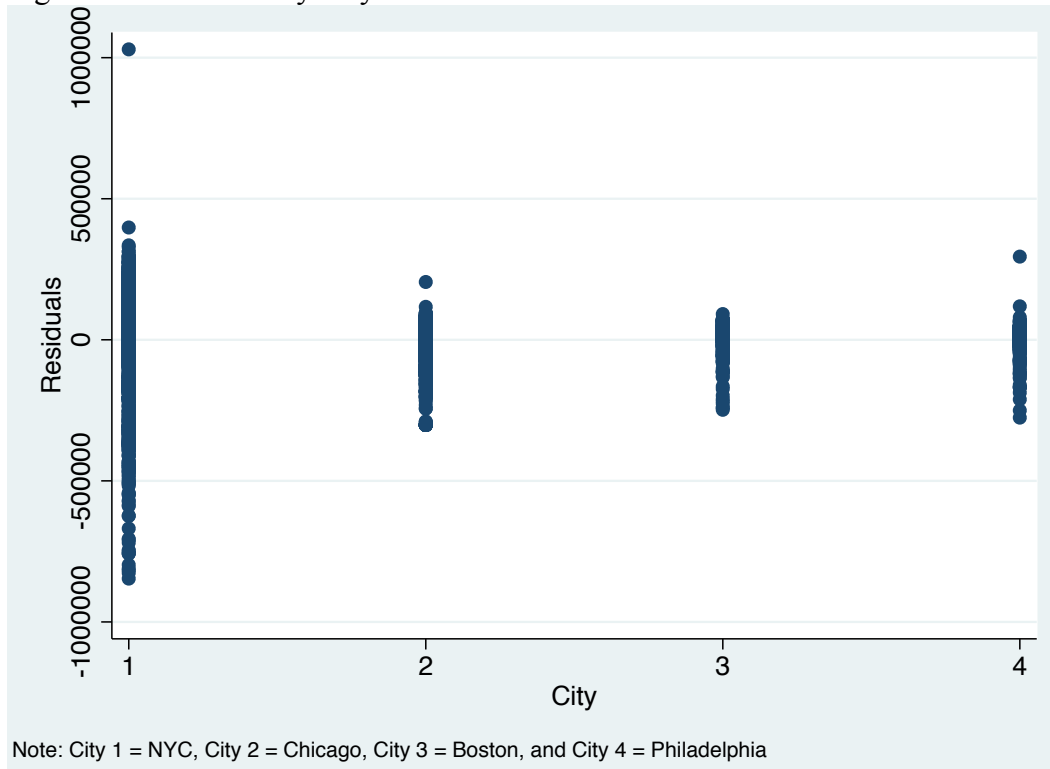


Figure 20: Residuals Against Unemployment

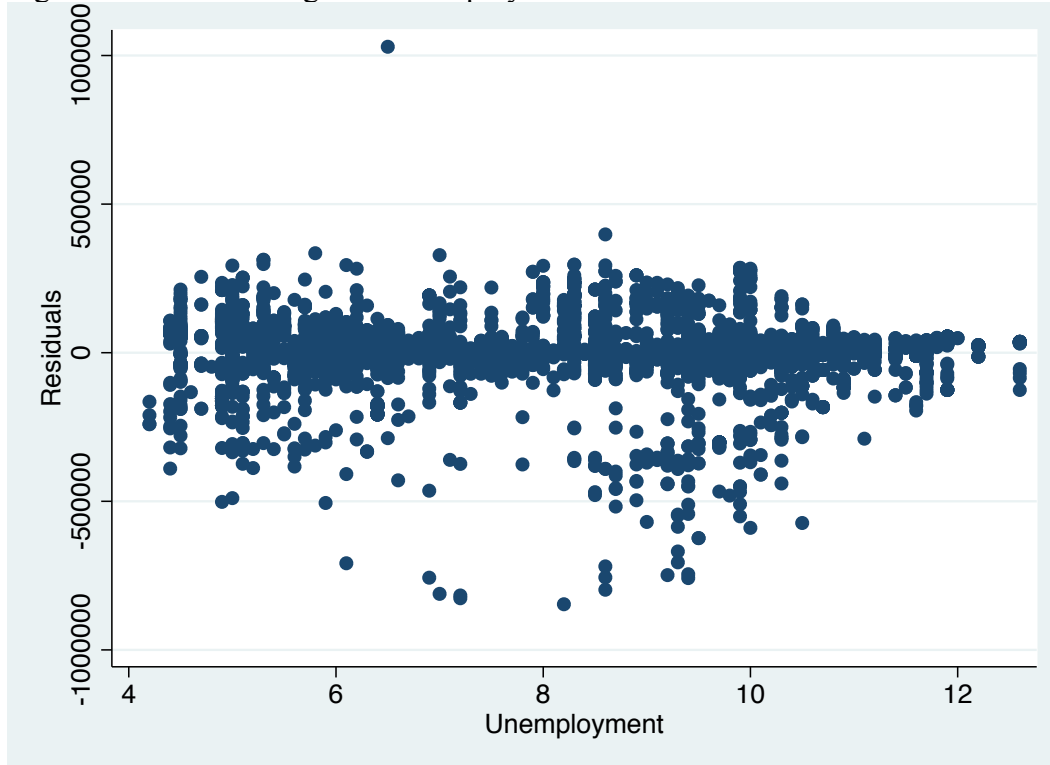


Figure 21: Residuals Against Gasoline Prices

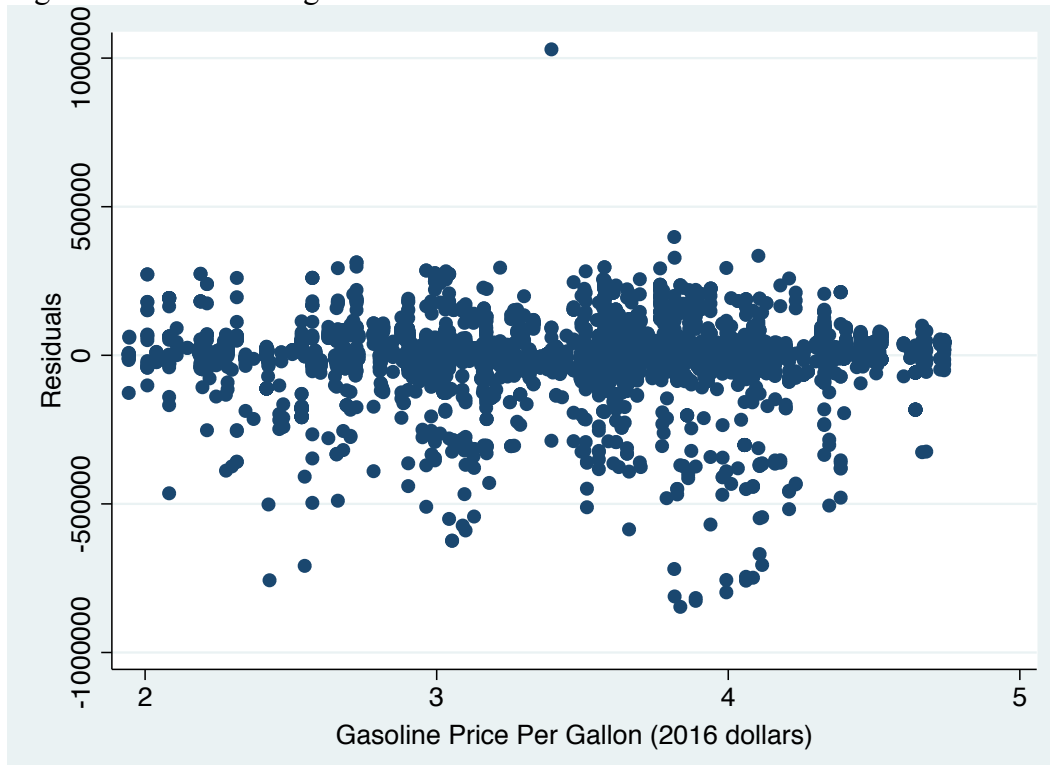


Figure 22: Residuals Against the Real Interest Rate

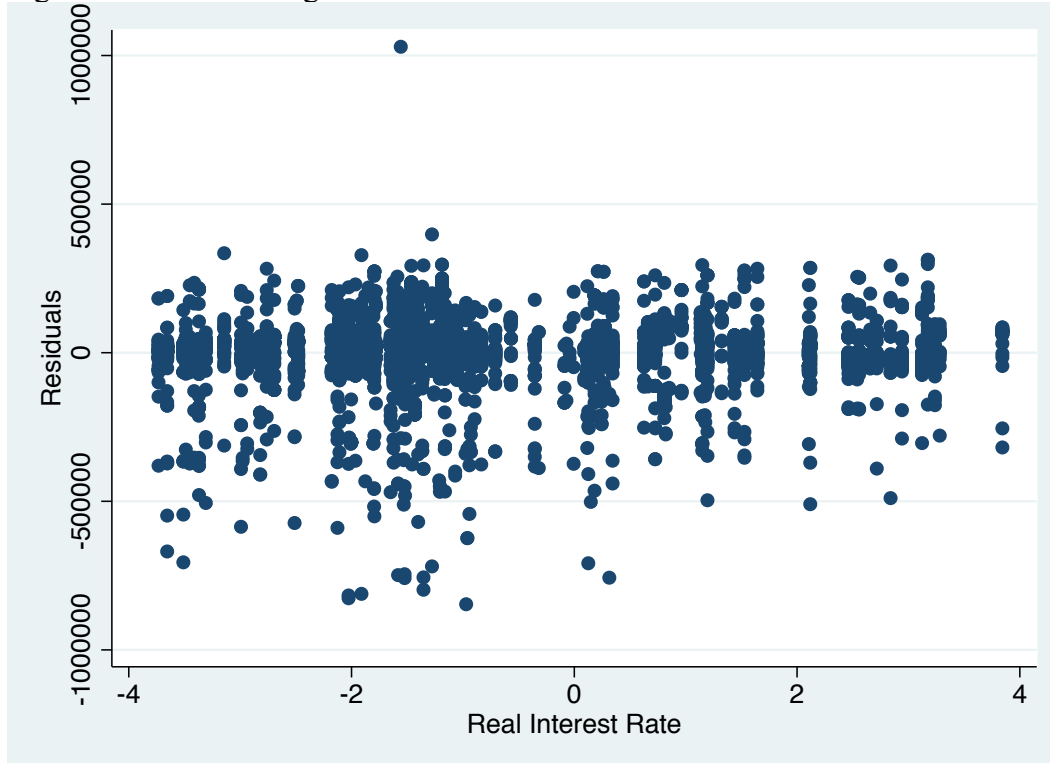
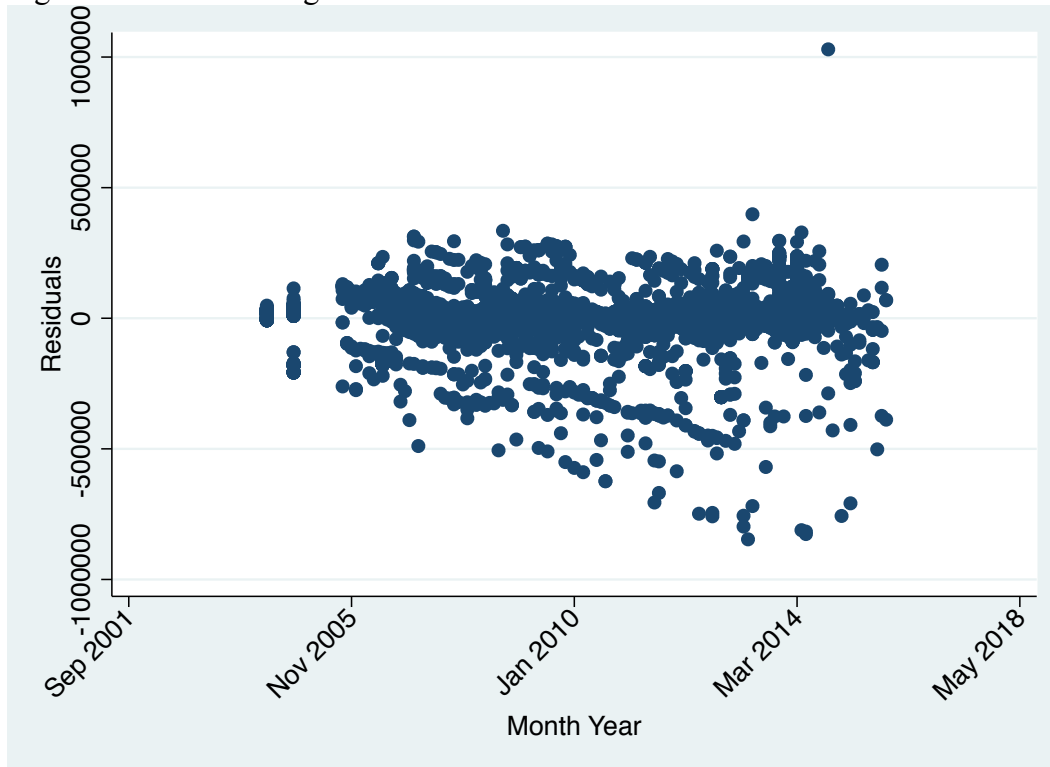


Figure 23: Residuals Against Time



APPENDIX E

RATIO MODEL SPECIFICATION RESULTS

Table 16 presents results from estimation with the ratio of the number of Uber drivers in a city to the number of taxi medallions rather than simply the number of Uber drivers in a city. This model should help normalize the effect of additional Uber drivers across cities with respect to differences in the number of medallions in each city. Results from specification 6 (presented in column 6) suggest that a one unit increase in the ratio of Uber drivers to medallions—e.g., an increase of 13,333 Uber drivers in NYC—results in a \$77,949 decrease in medallion values. Coefficient estimates of control variables generally agree with predictions but lack the desired statistical significance across the different specifications.

Table 16: Effect of Uber on taxi medallion values: Pooled Sample with ratio of Uber drivers to number of taxi medallions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ratio of Uber drivers to taxi medallions	134,164 (72377)	-68,725* (24689)	-49,514* (16982)	-54,366* (21682)	-75,035** (23290)	-77,949* (24612)
Wheelchair accessible medallion	266,442** (74286)	-6,649 (92957)	-70,664 (104654)	-88,026 (41983)	-96,712 (44209)	-96,828 (42959)
Alternative fuel medallion	-34,554 (29519)	-117,707* (40880)	-178,945* (61098)	-149,280** (41699)	-159,390** (42686)	-159,959** (41518)
Independent medallion	89,247 (141399)	39,234 (104644)	36,291 (95838)	-89,689*** (4791)	-87,559*** (5604)	-87,258*** (5483)
Auction	-86,911** (26114)	98,369 (41984)	188,188* (78390)	117,928 (56187)	133,474 (58741)	132,466 (56881)
Population	0.0576 (0.026)	0.0565** (0.017)	0.0576** (0.016)	0.346** (0.064)	0.0948 (0.202)	-0.00434 (0.214)
Unemployment rate	20,934 (14058)	-27,961 (13495)	-33,589 (15053)	-5,656 (2447)	-4,138* (1382)	-3,338* (1366)
Gasoline price per gallon	35,109 (27863)	-58,878 (27623)	-62,577 (29674)	-297 (5388)	-3,925 (5603)	-3,685 (5222)
Real interest rate	-11,811 (11519)	-6,705 (5546)	-6,077 (4866)	5,991 (3927)	5,067 (2943)	4,718 (2878)
Linear monthly time trend	No	Yes	Yes	No	No	No
Quadratic monthly time trend	No	No	Yes	Yes	No	No
City specific monthly linear time trend	No	No	No	No	Yes	No
City specific monthly quadratic time trend	No	No	No	No	No	Yes
City fixed effects	No	No	No	Yes	Yes	Yes
N	7,107	7,107	7,107	7,107	7,107	7,107
R ²	0.615	0.762	0.767	0.844	0.846	0.847

Notes: Robust standard errors clustered at the city level in parentheses, *** p<0.01, ** p<0.05, * p<0.1, Prices are in 2016 dollars using a quarterly GDP deflator, Observations from Philadelphia's 2015 auctions are dropped.