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An Empirical Study of Bicycle Sharing Systems Using a Product Diffusion Context

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by

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Abstract

This paper analyzes the adoption of bicycle sharing systems (BSSs) in a sample of five U.S. cities including Boston, Los Angeles, New York City, Portland OR, and Washington DC. This paper builds on studies of BSS usage that model usage as a function of city-specific variables. It expands on previous studies by placing the analysis of BSS usage in a product-diffusion context, the range of analysis is a time series spanning the first 36 month of each system's operation. This analysis seeks to develop a microeconomic model of incentives that predicts city-level usage as the collection of individual product adoption decisions. The adoption decisions are made in the presence of incentives to adopt, stemming from benefits of BSS as a transportation mode and from urban social dynamics. The incentive model is mathematically formulated as a city's representative agent's (RA's) transportation mode choice. The RA's level of BSS usage, measured as the portion of trips taken with the BSS, is utility-maximizing and is determined with a discrete choice model of transportation. The usage level is modelled as a function of select city-wide variables that correspond to the incentives that potentially influence BSS adoption decisions. This paper's empirical section tests the incentive model's predictions with time series regressions for each city over the span of the first 36 months of operation. The econometric model estimates that housing prices have a significant positive effect on BSS adoption, unemployment has an insignificant effect, and the member usage share has a significant negative effect on BSS adoption. The results of this paper identify the direction of factors relevant to BSS adoption in some of the sample cities. They also enable a relative comparison between cities, housing prices in Boston, for example, are predicted to have a relatively large effect on BSS adoption. Finally, the incentive model of urban product adoption developed in this paper can be expanded to carry out a more in-depth study of BSS or applied to help understand the adoption of an entirely different product.

1. Introduction

BSSs have emerged as ubiquitous and visible transportation options in cities around the world. BSS offers urban citizens and tourists an additional mode choice for transportation around the city. There are numerous benefits to consumers travelling via BSS—it is affordable, healthy, and seen as eco-friendly. Sustainability-conscious policy makers promote the creation and success of BSSs for similar health and environmental benefits.

The sample cities in this paper have third-generation BSSs. The characteristics of third-generation systems are secure docking stations and electronic access/payment of bikes. Their infrastructure has two main elements, a fleet of bikes and a network of docking stations. For a consumer to rent a bicycle, they go to a station and remove it from that start station using either a mobile payment or a pre-paid membership card. Consumers then ride the bicycle for a period of time and complete the interaction by docking the bike at an end station. Consumers can either drop the bike off at the original station as a round trip, or leave the bike securely at another station within the city. Docking stations are distributed at key locations throughout the city, ideally to maximize ridership considering both commuters and less frequent riders such as tourists.

The BSSs in the sample have a wide range of usage patterns. Part of this is driven by size, where larger cities have the demand pool to sustain a bigger network that gets increasing returns from scale. The low usage in Los Angeles, however, indicates that other factors like bike-ability are important. Below are usage summaries of trips per day (TD) for each of the five cities, one metric that this paper will employ. The distribution is comprised of monthly values from each of the 36 in the span of analysis.

Table 1: TD by City

	N	Mean	Std Dev	Min	Max
Boston	36	3,338	2,036	143	6150
Los Angeles	36	695	194	334	1,075
New York	36	25,337	10,006	7,033	42,990
Portland	36	941	544	212	2,561
Washington DC	36	4,609	2,376	133	9,316

An important aspect of BSS system adoption is the pricing scheme that incentivizes repeated users to purchase a membership. Cities offer relatively expensive customer rates for one-time rides for customers. For return users, there are monthly and annual subscriptions for an up-front payment and significant per-ride discounts. For reference, below are the 2020 prices for the cities in the sample.

Table 2: 2020 BSS Prices by City

	Boston	**Los Angeles**	**New York**	**Portland**	**Washington, DC**
Single Ride	$2.50	$1.75	$3.00	$.08/min	$2.00
Daily Pass	$10.00	$5.00	$12.00		$8.00
Monthly Pass	$20.00	$17.00		$19.00	$28.00
Annual Pass	$99.00	$150.00	$169.00	$99.00	$85.00

This paper will use membership to indicate a decision to adopt BSS as a mode of transportation. Membership is defined by those who purchase either an annual or monthly pass.[1]

2. Literature Review

This paper follows the method utilized in two papers that study BSS performance: Zhao et al. (2013) and Médard de Chardon et al. (2017). Zhao's paper investigates the effect of various city-level factors on the performance of BSS across China. Médard de Chardon's looks at BSS across the globe. This section will briefly summarize both papers, particularly their methodology. The section concludes by discussing how this paper's method aligns with and then builds on the previous two.

[1] New York City offers an annual pass only, no monthly passes.

Chinese BSS analysis

Zhao et al. (2014) set out to measure factors that influence BSS performance. They identify two relevant elements of performance: usage, measured by trips per day; and turnover, measured by trips per day per bike (TDB). The sample is of 68 Chinese cities and looks at data from a single month. TD indicates the absolute size of the BSS while TDB gets at efficiency by correcting for size and certain benefits to scale. The merits of TDB as a measure of BSS performance are discussed in Gauthier et al. (2013).

The paper runs regressions with both TD and TDB as dependent variables. It uses independent variables that fall into three categories: (i) urban features, (ii) system features, and (iii) composite features. The urban feature variables capture relevant characteristics of the urban economy of which the BSS is a part including employment, population, income, and government spending. The system characteristics are BSS-specific levels that might influence performance. BSS demand is a key one, measured by the number of members. BSS supply is also included, measured by the number of bikes and stations. The composite indicators combine city and BSS factors. One example is a ratio of the penalty for returning a bike late to income per capita, a sort of effective fine rate for a city's BSS.

The paper finds that members and docking stations both have a significant positive effect on turnover. Number of bikes has a positive effect on usage, but a negative effect on turnover ceteris paribus. This interesting result suggests an optimal number of bikes for a BSS that "should be neither too many nor too few" (Zhao, 262).

Global BSS analysis

Médard de Chardon et al. (2017) expands the analysis of Zhao (2014) to a global scope and extends the sample timeframe to a period of 12 months. It diverges from the previous paper and only uses turnover as the metric of performance, measured by the monthly average of TDB. The expansion to 12 months adds an important time element to the study.

For the empirical portion, Médard de Chardon (2017) uses monthly-TDB as the dependent variable. The paper proposes a long list of independent variables to consider—both time-constant and time-variant—that fall into the categories of urban features or system features. The study expands on Zhao (2014) by including additional variables in each category. The urban features section include data on transportation infrastructure such as miles of bike lanes. The system feature section includes important data on BSS distribution, such as the standard deviation of the docks per station variable. A high standard deviation indicates a BSS with a wide range of station capacity. This could lead to micro-shortages or micro-surpluses if demand across stations is unpredictable.

The final regression includes the following independent variables: operator type, standard deviation of docks per station, indicator for local helmet requirement law, log of population, wind speed, temperature, and cycling infrastructure. The paper found that non-profit ownership has a significant negative effect on performance. Another interesting finding is that variation in station size (dock number standard deviation) has a negative effect on performance. The proposed interpretation is that BSSs with large variation in station size might put too many resources into their large stations at the expense of quality and coverage for smaller ones.

Present contribution

This study's approach differs from Zhao (2014) and Médard de Chardon (2017) in three key ways. First, and most significantly, this paper motivates the empirical analysis with a microeconomic model of incentives that stresses the individual adoption decisions that collectively constitute the city's total BSS usage. Second, this paper uses data from the first three years of a BSS, which places it in a product diffusion context and provides a wider range of analysis. Third, the sample of cities narrows to consider only five, which enables a closer comparison between cities.

3. Incentive Model of Urban Product Adoption

3.1) Product Incentives to BSS Adoption

The total adoption of BSS in a city comes from the aggregate of each individual's decision to use BSS as a means of transportation. Therefore, to analyze the city-level of adoption, it is essential to understand the incentives that drive BSS adoption for individuals. This model accounts for two types of incentives, product incentives and urban consumption incentives. The product incentives arise from features of the product, for BSS these include low cost transportation, viability as a transportation alternative, and health/sustainability benefits. The urban consumption incentives arise from the economic geography of the city in which consumers make their adoption decision, decisions not made independently but rather as part of a transparent group.

Low cost transportation

Demographic studies have found that bikeshare users, especially in comparison to traditional cyclists, bike for utilitarian reasons. Buck et al. (2013) finds that among DC riders, BSS riders are lower income and more likely to ride for utilitarian reasons. Bike sharing replaces public transportation and walk trips. This aligns with the intuition from a Vancouver study that finds that the high-volume 'super-users' of the BSS are predominantly low-income (Winters et al. 2019).

Operators are able to price BSS as a low-cost option in part due to their business model. The storage model of secure docking stations shifts ownership costs from riders to the BSS operator. This allows riders to forego security costs like bike locks and transfer the risk exposure to a major concern like theft. They can also avoid the storage cost of owning a bicycle, often high in cities where space is expensive. The internalization of these costs in the BSS operator enables benefits to scale. They enjoy lower per bike ownership costs in the same way as commercial lessors by reducing average costs for acquisition, storage, and maintenance (Gavaazza 2010).

Viable transportation alternative

In addition to low-cost, BSS offers a viable alternative to other modes of transportation. A survey of new bikeshare users in New York City cite 'getting around faster' and 'saving money on transportation' as primary motivations for using bikeshare as transportation (Reilly et al. 2020). Operators recognize the potential benefits of biking, especially in places with downtown traffic problems. For all of the city systems analyzed in this paper, a key message of their marketing strategy is that bikeshare can, "get you there fast."

Health and sustainability

Health and sustainability benefits to bicycling also incentivize BSS. A survey study of the Vancouver BSS, Mobi by Shaw Go, explores the motivations of near users—those not currently using but interested in bikeshare—to become BSS members Hosford et al. (2018). The study finds that near users tended to be motivated by health benefits, not owning a bicycle and proximity to stations. There is also a perception of sustainability that incentivizes BSS adoption. With that said, Médard de Chardon (2019) has an interesting study in which he argues that although BSSs are plausibly sustainable there is evidence that (i) they enhance inequalities by servicing privileged users and (ii) they do not render significant environmental benefits. Nevertheless, the perception of sustainability, even if unfounded, is enough to provide the incentive.

3.2) Urban Consumption Incentives to BSS Adoption

In addition to the individual incentives to BSS discussed above, the crowded and visible nature of urban consumption provides product-external incentives to BSS adoption. The proximity of urban consumers enables preference exchange from existing BSS users to prospective ones. Schoner (2016) studies how adjacent behavior affects an individual's decision to participate in bikeshare. The paper finds a small contagion effect of BSS users transmitting their preferences to consumers who they contact, such as coworkers and friends. The visibility of urban consumption could incentivize BSS adoption via social returns. One such example is conspicuous conservation, where the utility of a good increases with the visibility of its consumption (Heffetz, 2004). Another social return could come from peer pressure and motivation, what Ravina (2019) refers to as external habit. The communal popularity of biking likely incentivizes BSS adoption beyond a level determined only by its in-a-vacuum product features.

3.3) Stylized Example: Follow the Leader Adoption

A stylized anecdote will help develop some intuition for how the characteristics of BSS and the dynamics of urban consumption might lead an individual to adopt BSS as a mode of transportation. Consider a marginal citizen's decision of how to commute to work. They have traditionally taken the subway or an Uber from time to time. A coworker, however, has been raving about the city's new BSS, EZbike, and its effect on his physical and mental health. The commuter noticed that there is even a docking station a block from the office—closer than the subway. The cost to test the system is low, $3 for each leg of the ride to and from work, significantly cheaper than an Uber. So, one day when it is nice out, the commuter decides to try his coworker's recommendation and takes EZbike to work.

This stylized example highlights a few elements of the diffusion of BSS networks through social channels. First, users of the system want to be visible since BSS has elements of conspicuous consumption. This incentivizes interactions like a coworker promoting their decision to use the BSS. Second, use of the BSS is functionally interchangeable with other transportation options and the barrier to entry is low. The commuter is able to try out the BSS without committing to a full membership, and it even comes at a lower cost than an existing alternative like Uber. Collectively, these factors enable the transmission of BSS mode choice from an existing user to a potential one with a low transaction cost.

Were the cost of using the BSS for the first time higher, adoption driven by preference exchange could be less likely. What if the product to be exchanged was solar panels? The information transfer to inform the adoption decision for solar panels is much more difficult. There are environmental considerations, a buy-back mechanism with the power grid, and financing options to be considered. This relative difficulty of information exchange can be understood as a high transaction cost for the exchange of preferences from the leader to the follower. Additionally, the cost of solar panels is much higher than testing the BSS. As a result, a potential consumer cannot as easily test the new product without committing to it.

In summary, BSSs seems susceptible to a follow-the-leader dynamic of diffusion due to the low-cost of preference exchange and the low barrier to entry of prospective users. This preference exchange contributes to the important role of the urban consumption environment in determining BSS adoption. Additionally, the presence of this sort of mechanism could introduce a self-perpetuating dynamic to BSS adoption.

4. Mathematical Formulation

4.1) Representative Agent Utility Maximization

A city's adoption of a BSS can be understood as the mode share of BSS. Mode share is a percentage of total trips, in this case given by the number of trips made using BSS in the city divided by the total number of trips made in the city (1).

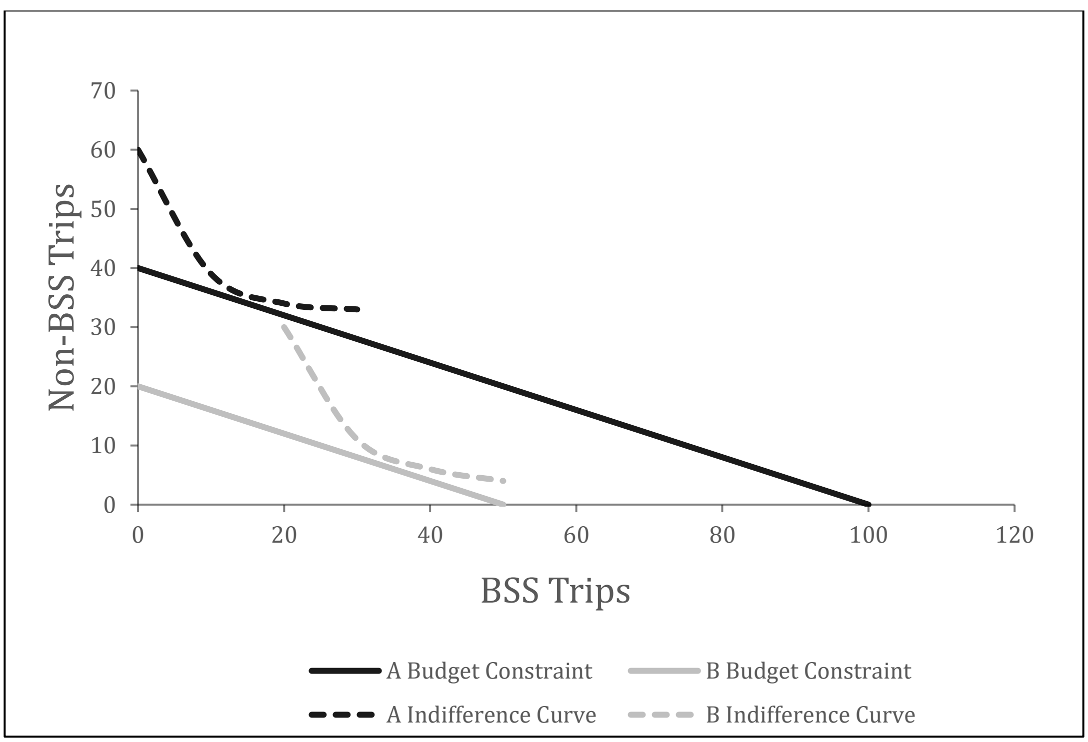
$$modeshare_{bss} = \frac{trips_{bss}}{trips_{total}} \quad (1)$$

The mode share of BSS can be modelled by a microeconomic utility maximization problem. The city's transportation decision is modeled by a representative agent's choice of the number of trips taken with the BSS and the number of trips taken with all other options. The RA's optimal mode share occurs at the highest indifference curve subject to the budget constraint.

The incentives to BSS adoption discussed above enter into the RA's transportation decision through the utility function and the budget constraint. Different characteristics of cities will result in different BSS mode share choices. To demonstrate, consider the result from Buck (2013) and Winters (2019) that BSS users tend to be low income. A corollary of their result is that transportation via BSS is an inferior good, whose quantity demanded increases as income drops. For a graphical illustration, consider two cities each with a new BSS. They both have densely populated downtowns with surrounding residential industrial areas. The difference is that City A has a relatively wealthy population compared to City B. Urban workers tend to have white collar jobs in City A and blue collar jobs in City B.

Figure 1 demonstrates a simple utility maximization problem. The price of a BSS trip is $2 and the average price of a non-BSS trip is $4. City A's RA has a transportation budget of $200 and City B's RA has one of $100. The wealth differential between the cities is reflected in their budget constraints, City B's budget constraint has the same slope as City A's, but it is shifted towards the origin, corresponding to a lower purchasing power. The assumption that the budget constraints have the same slope can be relaxed to account for potentially lower costs in cities with more transportation options. The budget constraints then interact with each RA's utility function, reflecting each RA's unique preferences, to determine the number of trips taken with the BSS and the number of trips taken with other methods. Additionally, each RA face a similar floor for trips in a month, set around 40 for commutes to and from work. City B's RA relies more on the cheaper BSS to meet their monthly transportation needs, it selects 35 BSS trips and 6 non-BSS trips. City A's RA has the luxury of transportation via non-BSS trips, it selects only 15 BSS trips and 34 non-BSS trips.

Figure 1: Utility-Maximizing Transportation Choices for Cities A and B



4.2) Discrete Choice Model for Transportation

Underlying the utility framework outlined above is a discrete choice model as developed in McFadden (1974). It relates a given mode of transportation's share of total transportation to the utility derived from using the given mode of transportation (2). In the context of BSS in a city, the utility derived from using the BSS predicts the portion of total trips taken with the BSS as opposed to *K* other options like car, rideshare, transit, or walking.

$$P_{bss} = \frac{e^{u_{bss}}}{\sum_K e^{u_k}} \quad (2)$$

It is a disaggregate demand model in that it takes individuals as the basic unit of observation and aggregates to define the population choice with a single set of parameters. The population mode-share utility come from the summation of individual utilities (3).

$$u_{i,bss} = v_{i,bss} + e_{i,bss} \quad (3)$$

This paper diverges from a typical model of transportation mode choice in that it does not attempt to model the utility from all possible transportation mode choices. Were that the case, it would require estimates of the utility from trips taken by car, by Uber, by walking, etc. These non-BSS utility estimates would all take the form of Equation 3 and they would all appear in the denominator sum of Equation 2 to determine the mode share of BSS. They could be estimated using data from a sample of individual transportation choices where, for example, of the 100 observations, 35 transport via car, 25 public transportation, 25 walk, and 15 BSS. Due to data considerations, this paper does not attempt to estimate the utility from every transportation mode. Instead, this paper makes a simplifying assumption that individuals choose between transportation via BSS and transportion via any non-BSS option. As a result, the relationship between BSS mode share and utility from BSS does not take the functional form of Equation 2. Instead, the relationship between BSS mode share and utility from BSS takes a proportional form (4).

$$P_{bss} \approx u_{bss} \ (4)$$

Crucially, this simplified proportional form reflects the positive relationship between the BSS mode share and BSS utility, which creates a link between BSS usage and the system factors that determine BSS utility. The systematic component of an individual's utility from BSS is represented as *v* in Equation 3. It is determined by city characteristics that impact BSS utility, such as quality of city infrastructure and economic conditions. The unique part of individual utility not represented in the systematic component is represented by *e*, a random individual term. The random term accounts for individual heterogeneity such as behavioral preferences.

The mean utility for transportation via BSS in a city of population N is the average of individual utilities (5). As with the individual utilities, the mean utility can be represented with a systematic and random component (6).

$$\overline{u_{bss}} = \frac{\sum_{i=1}^{N} u_{i,bss}}{N} \quad (5)$$

$$\overline{u_{bss}} = \overline{v_{bss}} + \overline{e_{bss}} \quad (6)$$

The mean utility for a given transportation mode can be estimated with the mean of the systematic component of utility. That systematic component is a function of the economic factors with which this paper is concerned (7).

$$\overline{u_{bss}} \approx \overline{v_{bss}}(member\ share, unemployment, housing\ prices) \ (7)$$

The utility maximization and discrete choice models are linked by the RA's BSS mode choice. The share of BSS in a city's transportation is the level that maximizes the RA's utility. In the discrete choice model, it is defined by the RA's mode share utility ratio, determined by the utility from BSS in the numerator and the sum of utilities from all transportation modes in the denominator (8).

$$P_{bss}^{*} = argmax(U_{RA}) = \frac{e^{\overline{u_{bss}}}}{\sum_{K} e^{\overline{u_k}}} \quad (8)$$

The RA's utility from the BSS is linked to the relevant city characteristics by the estimation of *u* with *v* (6). Together, these models provide a theoretical grounding for predicting BSS usage from city characteristics that correspond to the factors that incentivize bikeshare usage.

5. Sample Selection

The sample consists of five US cities including Boston, Los Angeles, New York City, Portland, OR, and Washington, DC. The cities were selected to provide variability based on climate, urban layout and bike-ability. Data availability also informed the selection process.

Climate

Weather plays an essential part in BSS adoption since biking is only viable in certain conditions. The sample therefore contains cities of varying temperatures and wetness. The presence of a cold winter is perhaps the most important climate factor, this is reflected in sharp seasonality for BSS usage in the northern cities, with a significant drop during the winter months. Southern cities like Los Angeles and Washington, DC have much more consistent usage year-round. Table 3 presents monthly temperature and rainfall over each city's range of analysis. Climate data come from the National Centers for Environmental Information (NCEI).

City layout

City layout plays an important role in the viability of biking. Cities with populated central business districts, walking cities like Boston and New York City, have many destinations densely concentrated and therefore accessible by bike. Los Angeles, by comparison, is typically classified as a driving city and has its destinations spread over a larger geographic area. That wider spread makes biking a less viable transportation option.

Table 3: Monthly Mean Temperature and Total Precipitation by City

n=36	Boston	Los Angeles	New York	Portland	Washington, DC
Temperature Fahrenheit	52.5 (16.4)	67.0 (6.8)	55.8 (16.8)	55.2 (11.7)	60.0 (15.9)
Precipitation Inches	3.09 (1.25)	1.18 (2.06)	3.81 (1.93)	3.02 (2.56)	3.37 (2.18)

(standard deviation)

Bike-ability

The company Walk Score calculates a Bike Score for major cities to in an attempt quantify bike-ability. The calculation considers four factors, bike infrastructure, topography, connectivity, and bicycle mode share. This sample consists mostly of cities that are seen as bike friendly. All rank in the top 10 for Bike Score among US cities except for Los Angeles, which is included as a datapoint of a less bikeable city.

Table 4: 2020 Bike Scores by City

	Boston	Los Angeles	New York	Portland	Washington, DC
Bike Score	70.5	58.7	70.0	82.4	70.7

6. Data

6.1) Overview

The BSS data come from public databases created and maintained by the BSS operators including Bluebikes in Boston, Metro Bike Share in Los Angeles, Citi Bike in New York City, BIKETOWN in Portland, and Capital Bikeshare in Washington, DC. Unemployment and housing price data come from the Federal Reserve Economic Data (FRED). Climate data come from the NCEI. This paper uses data for the first 36 months of each city's BSS. The cities introduced their bikeshare systems at different times, so the 36 months span different periods of time. The 3-year ranges, which all fall between September 2010 and June 2019, are presented below. Average values and standard deviations of regression variables are also presented below.

Table 5: Three Year Periods by City

	Boston	**Los Angeles**	**New York**	**Portland**	**Washington, DC**
Start Month	January 2015	July 2016	June 2013	July 2016	September 2019
End Month	December 2017	June 2019	May 2016	June 2019	August 2013

Table 6: Summary Statistics of Regression Variables by City

n=36	**Boston**	**Los Angeles**	**New York**	**Portland**	**Washington DC**
TDB	2.43 (1.21)	0.65 (0.15)	4.00 (1.41)	0.97 (0.54)	3.29 (1.22)
TD	3,338 (2,036)	695 (194)	25,337 (10,006)	941 (544)	4,609 (2,376)
Member share	.781 (.100)	.593 (.077)	.891 (.074)	.498 (.143)	.809 (.065)
Unemployment	3.75 (0.57)	4.40 (0.43)	6.09 (1.10)	3.96 (0.34)	5.91 (0.32)
HPI	190.51 (9.63)	270.51 (12.36)	175.92 (3.83)	224.04 (10.22)	186.37 (7.31)
Temperature	52.5 (16.4)	67.0 (6.8)	55.8 (16.8)	55.2 (11.7)	60.0 (15.9)

(standard deviation)

6.2) Dependent Variables

Trips per day per bike

TDB for each month is estimated with the available trip data (9). To account for a unit root in the time series, TDB is transformed to its growth rate (Figure 2). Data limitations make the TDB estimate somewhat unreliable. The challenge is the number for total bikes. The operators do not provide a number for fleet size by month, so it is estimated by the number of unique bikes used in all the trips taken in the month. For unique bikes to be an accurate substitute for fleet size, all bikes in the fleet would have to be used at least once each month. The assumption does not appear to hold, as illustrated by swings in the number of unique bikes driven by seasonal factors (Figure 3).

The shortcomings of the fleet size metric restricts the usefulness of TDB as a measure of system efficiency, as used in Zhao (2014) and Médard de Chardon (2017). With that said, it remains a potentially useful indicator of efficiency, if not an accurate measure of it. This paper will use it in regression but proceed with caution.

$$TDB = trips\ in\ month\ /\ days\ in\ month\ /\ total\ bikes \quad (9)$$

Table 7: Monthly TDB Growth by City

n=35	Boston	Los Angeles	New York	Portland	Washington, DC
g_TDB	.123 (.551)	.022 (.217)	.054 (.301)	.109 (.544)	.147 (.570)

(standard deviation)

Figure 2: Monthly TDB Growth by City

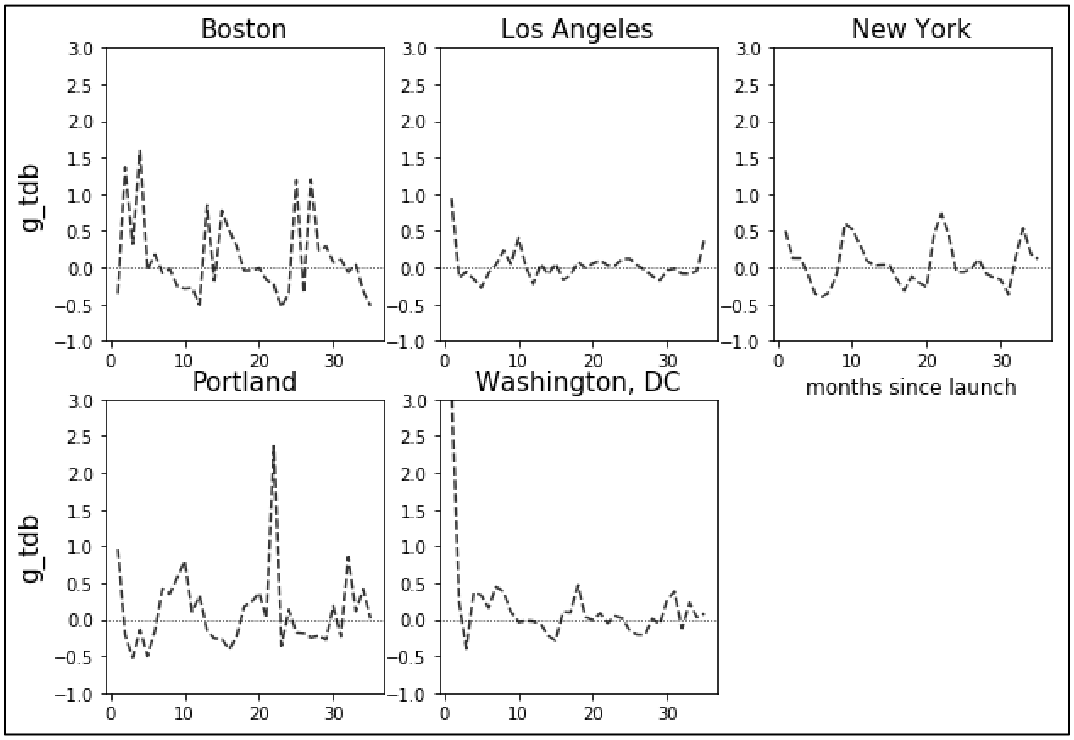
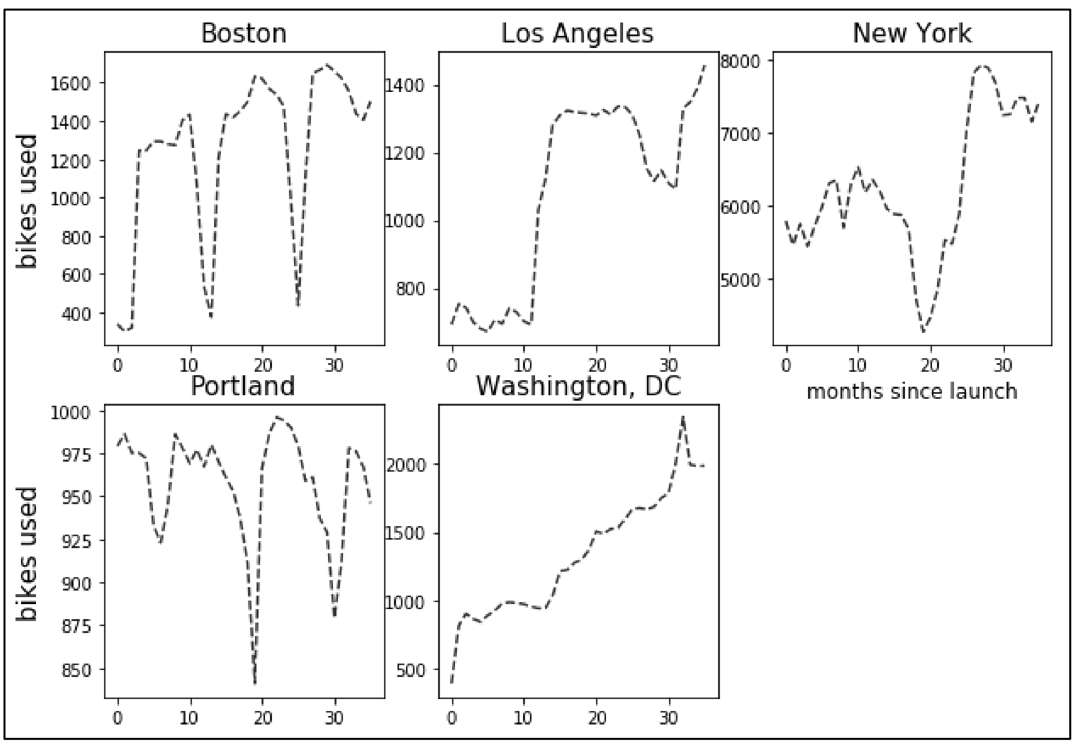


Figure 3: Monthly Bikes Used Over Time by City



Trips per day

TD is used as a measure of absolute BSS usage (10). As a strict measure of usage, TD sacrifices the partial control for BSS size afforded by TDB. On the other hand, by not using fleet size in its calculation, it avoids the uncertainty from the estimate of TDB. To account for a unit root in the time series, TD is transformed to its growth rate.

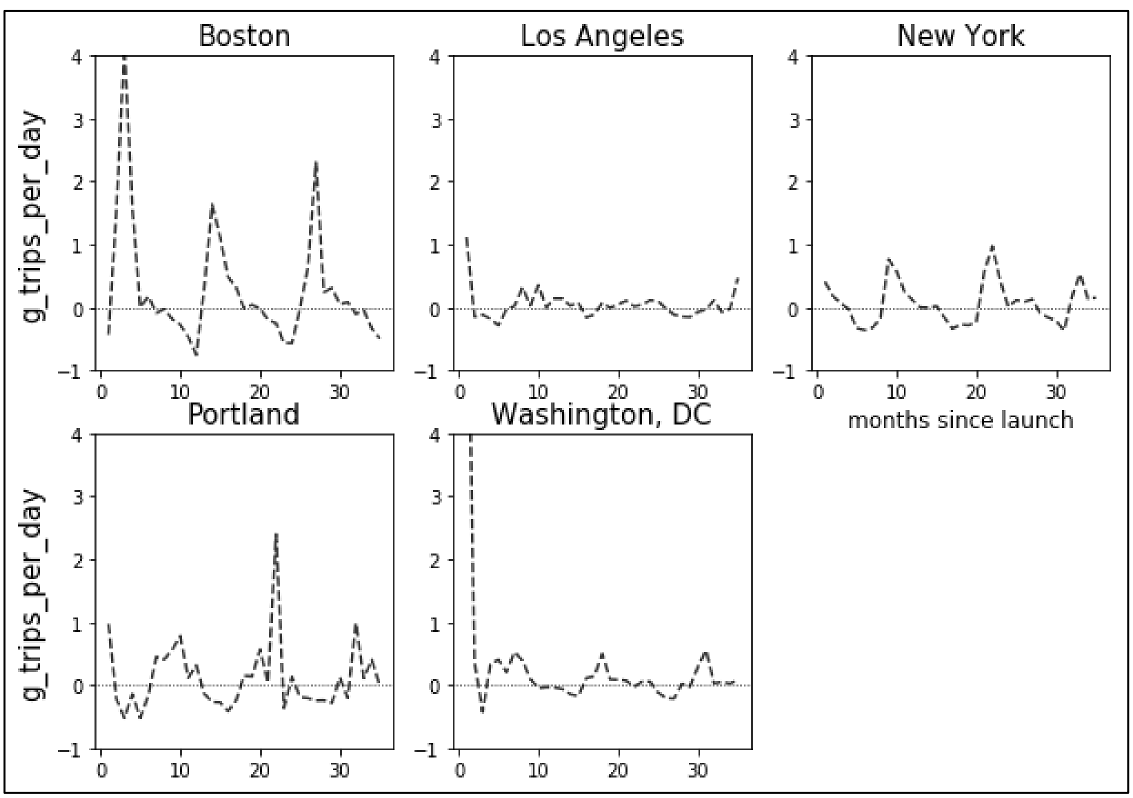
$$TD = trips\ in\ month\ /\ days\ in\ month \quad (10)$$

Table 8: Monthly Growth Rate of TD by City

n=36	**Boston**	**Los Angeles**	**New York**	**Portland**	**Washington, DC**
g_TD	.288 (.960)	.047 (.241)	.068 (.336)	.113 (.560)	.303 (1.30)

(standard deviation)

Figure 4: Monthly TD Growth by City



6.3) Independent Variables

Member share

For each month, this paper calculates a member share statistic, equal to the ratio of trips taken by members to total trips (11).

$$\textit{Member share} = \textit{member trips} / \textit{total trips} \quad (11)$$

The member share metric is designed to measure the adoption level in each city, under the assumption that purchasing a membership indicates the choice of BSS as a mode of transportation. It is worth noting that the member share is grounded in usage, rather than straight user counts. The member usage ratio is likely higher than a ratio of the number of members to total users of the system. This is because a member punches above their weight, as it were, in that a single member, in general, will take far more rides per month than a single customer.

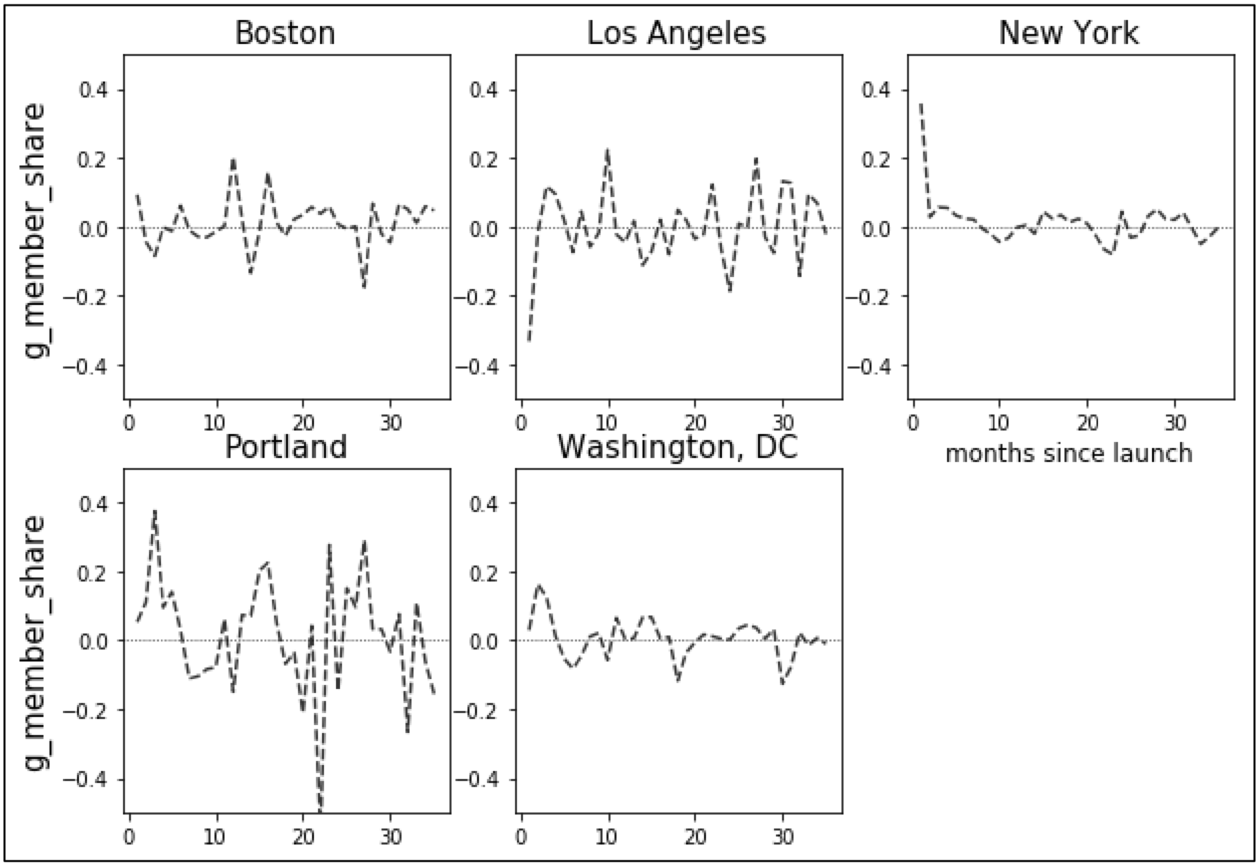
Member share is expected to have a positive effect on usage. The follow the leader element of bikeshare adoption suggests that increasing member share will build upon itself to bring in more members. Coupling this dynamic with the fact that members are higher volume users of the BSS, increasing member share should increase usage.

Table 9: Monthly Growth Rate of Member Share by City

n=35	**Boston**	**Los Angeles**	**New York**	**Portland**	**Washington DC**
g_member_share	.012 (.070)	-.002 (.108)	.013 (.069)	.015 (.175)	.004 (.058)

(standard deviation)

Figure 5: Monthly Member Share Growth by City



Unemployment

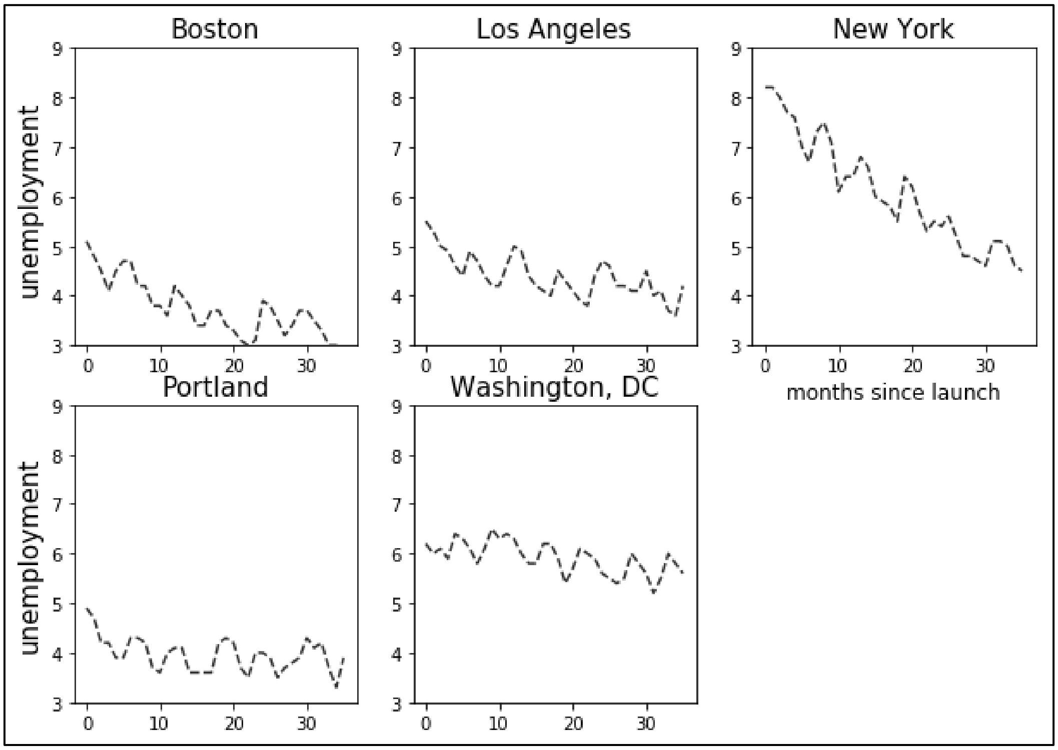
Unemployment data are monthly and come from FRED. The geographic unit of analysis is the metropolitan statistical area (MSA). Boston's MSA, for example, extends to Cambridge, MA and Nashua, NH. [2]

The expected correlation of unemployment with bikeshare usage is ambiguous. As discussed above and pointed out in papers like Winters (2019), frequent BSS users choose it because it is a low-cost transportation option. In so far as an increase in unemployment decreases income in the aggregate, the effect on BSS usage seems positive. The aggregate hit to income from an increase in unemployment would make transportation via the BSS more attractive as new members search for low-cost transportation options. On the other hand, bike share superusers tend to be

[2] U.S. Bureau of Labor Statistics, Unemployment Rate retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org.

commuters and blue collar workers. Blue collar jobs are at relatively high risk on the margin, so an increase in unemployment could leave a relatively high portion of frequent bikeshare users without work and therefore without need to commute via the BSS.

Figure 6: Monthly Unemployment Rate by City



Housing prices

Housing prices are measured on a monthly basis using the S&P/Case-Shiller Home Price Index (unadjusted), also retrieved from FRED. The housing price data are at the city level. [3]

The expected effect of housing prices on bikeshare usage is also ambiguous. An increase in housing prices would seem to increase BSS usage in so far as higher prices for renters might hit their incomes in the same way as unemployment, therefore making them more likely to seek out low-cost transportation. In this type of short run, when demand for housing is relatively inelastic, BSS usage might experience an uptick. When consumers have the opportunity to adjust to the new higher prices, the portion of wealthy consumers in a city might increase as low-income

[3] S&P Dow Jones Indices LLC, S&P/Case-Shiller Price Index], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org.

households are priced out. This larger portion of wealthy consumers could have opposing effects on BSS usage. The drain on low income households would tend to decrease the number of high-usage members of the BSS and drive down usage. The increase in wealthy consumers could bring in what could be called luxury riders, that use the BSS system to enjoy health or sustainability benefits. This class of luxury riders would also seem to benefit from the conspicuous consumption of transportation via BSS.

Temperature

Temperature data came from the National Centers for Environmental Information (NCEI). This paper uses monthly averages for city level data found in the Global Historical Climatology Network - Daily database. [4]

Relatively higher temperatures are expected to have a sizable positive effect on bikeshare usage. Given the degree of exposure from bicycling, its viability as a transportation option is largely determined by weather conditions. This dependence can be observed in the seasonal usage fluctuations for all cities in the sample. Temperature is included primarily to control for the seasonality of BSS usage.

[4] Menne, Matthew J., Imke Durre, Bryant Korzeniewski, Shelley McNeal, Kristy Thomas, Xungang Yin, Steven Anthony, Ron Ray, Russell S. Vose, Byron E.Gleason, and Tamara G. Houston (2012): Global Historical Climatology Network - Daily (GHCN-Daily), Version 3. [indicate subset used]. NOAA National Climatic Data Center. doi:10.7289/V5D21VHZ [access date].

Figure 7: Monthly HPI Growth by City

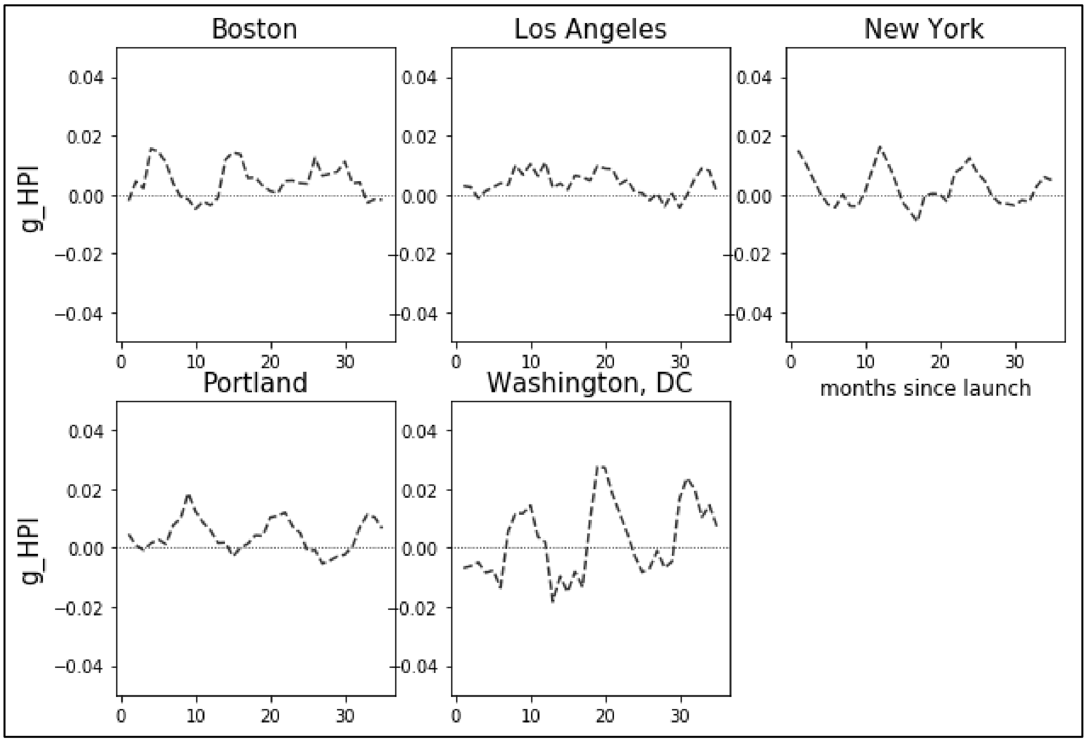
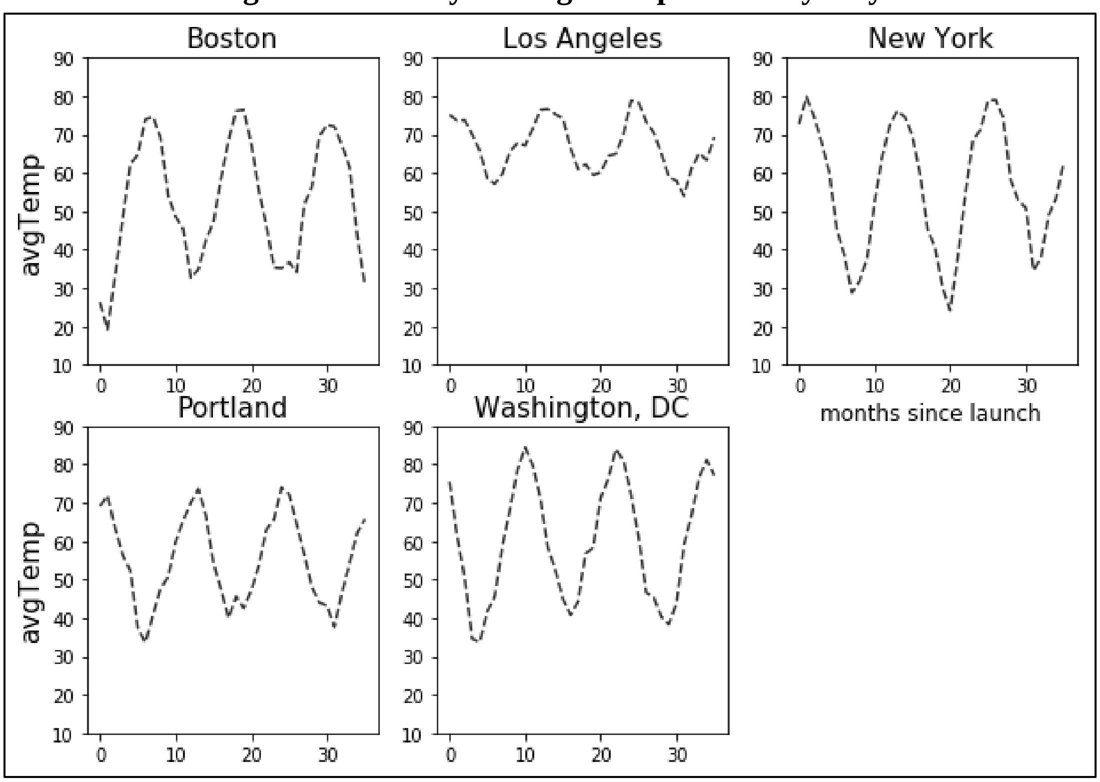


Figure 8: Monthly Average Temperature by City



7. Econometric formulation

7.1) Overview

This paper's econometric specification defines a city's BSS usage to that city's economic factors via the discrete choice model outlined in section 5. Usage is measured with both TDB (12) and TD (13). It is estimated in a total of 10 regressions, 5 for each sample city with the two dependent variables.

$$g\_TDB_t = \beta_0 + \beta_1 g\_member\_share_t + \beta_2 unemployment_t + \beta_3 g\_hpi_t + \beta_4 temperature_t + e_t \quad (12)$$

$$g\_TD_t = \beta_0 + \beta_1 g\_member\_share_t + \beta_2 unemployment_t + \beta_3 g\_hpi_t + \beta_4 temperature_t + e_t \quad (13)$$

The regression is ordinary least squares and the results indicate the directional effect that each independent variable has on BSS usage. Since BSS usage is not equal to the estimated quantity in the regression equation, the magnitude of slope coefficients does not indicate a one-unit level increase.

7.2) Stationarity

The dependent variables TD and TDB are both transformed to their growth rates to address non-stationarity in their levels. A Dickey Fuller test of each variable's level indicated the presence of a unit root. The differencing embodied in the growth transformation corrected for the unit root, and both growth variables have stationary time series.

Table 10: Dickey Fuller Statistics by City

	Boston	Los Angeles	New York	Portland	Washington, DC
TDB	-2.11	-2.86*	-1.96	-2.64*	-2.41
g_TDB	-5.93***	-7.85***	-3.20**	-5.77***	-14.41***
TD	-1.99	-2.13	-1.57	-2.66*	-0.91
g_TD	-3.31**	-8.40***	-3.08**	-5.70***	-32.96***

*p<.10, **p<.05, ***p<.01

The independent variables member share and housing prices are also transformed to growth rates.

7.3) Seasonality

The dependent variables of BSS usage as well as the explanatory member share variable are subject to seasonal fluctuations, especially in the northern cities. Temperature is included as an explanatory variable to account for the effect of monthly changes in weather on usage.

8. Results

8.1) Summary

The time series regressions for TDB (Table 11) and TD (Table 12) indicate that housing prices and the growth of member share have a significant effect on usage for some of the cities. The coefficient on the growth of member share is negative for all significant results, the opposite of what the incentive model predicts. The housing price variable is positive for all significant results, which updates the incentive model’s ambiguous prediction. Unemployment and temperature have an insignificant effect on usage across the board. The insignificant effect of unemployment is consistent with the incentive model’s prediction that unemployment would have an ambiguous effect on BSS usage.

Table 11: Regression of TDB
Time series for the first 36 months of BSS

g_tdb	Boston	Los Angeles	New York	Portland	Washington, DC
g_member_share	-2.12	-0.48	-0.82	-2.21***	-1.90
	(1.28)	(0.37)	(0.79)	(0.36)	(1.91)
Unemployment	0.18	0.07	-.003	0.06	0.21
	(0.17)	(0.11)	(.052)	(0.17)	(0.34)
g_HPI	31.26*	4.86	19.71*	19.69*	-4.61
	(16.14)	(9.21)	(10.58)	(11.28)	(11.49)
Temperature	-.001	.005	.001	.001	.002
	(.005)	.006	(.004)	(.004)	(.008)
constant	-0.57	-0.59	-0.01	-0.54	-1.18
	(0.70)	(0.51)	(0.40)	(0.75)	1.95
N	35	35	35	35	35
F	2.63*	1.31	1.97	20.43***	0.38
R-squared	.26	.15	.21	.73	.05

*p<.10, **p<.05, ***p<.01
(standard errors)

Table 12: Regression of TD
Time series for the first 36 months of BSS

g_td	**Boston**	**Los Angeles**	**New York**	**Portland**	**Washington, DC**
g_member_share	-7.60***	-0.81**	-1.27	-2.27***	-1.75
	(1.92)	(0.37)	(0.88)	(0.36)	(4.45)
Unemployment	0.17	0.11	-.000	0.08	0.08
	(0.25)	(0.11)	(.058)	(0.17)	(0.80)
g_HPI	46.62*	12.75	20.12*	21.45*	-17.23
	(24.33)	(9.11)	(10.58)	(11.35)	(26.73)
Temperature	-.008	.006	.002	.006	.008
	(.011)	.006	(.004)	(.005)	(.019)
constant	-0.01	-0.86	-0.04	-0.62	-0.61
	(1.06)	(0.51)	(0.45)	(0.75)	4.53
N	35	35	35	35	35
F	6.02***	3.59**	2.11	21.70***	0.14
R-squared	.45	.32	.22	.74	.02

*p<.10, **p<.05, ***p<.01
(standard errors)

8.2) Member Share Growth Rate

Across the board there is a negative coefficient on the growth rate of the member share. In the regression of TDB, it is significant at the 1% level for the Portland time series. In the regression of TD, it is significant at the 1% level for the Boston and Portland time series' and at the 5% level for the Los Angeles time series. The -2.27 statistic on member share for the Portland regression of TD predicts a 2.27 drop in the growth rate of TD for a 1-point increase in the growth rate of the member share.

The negative coefficient on member share is contrary to the incentive model's prediction that usage would increase with the member share. This result could be indicating an omitted variable bias in which an important predictor of the growth rate in BSS usage is not included in the econometric specifications. Given the large seasonal fluctuations of the dependent variable, the omitted variable(s) could be necessary to properly identify the effect that season has on usage. Correcting for the omitted variable(s) could result in different coefficients on the existing member share and temperature variables. When the model is correctly specified, the coefficients on member share and temperature should support the fairly strong intuition that those variables have significant and positive effects on usage.

The surprising member share result could also reveal that the member share is not an effective proxy for the number of members in the BSS. Recall from Equation 11 that the member share is defined as the ratio of trips taken by members in the month to total trips taken in the month. This leaves it subject to serious seasonal fluctuations. When usage drops for cold months, member share spikes because the remaining BSS users are almost exclusively members who rely on it for essential transportation. As a result, any relationship that may exist between the number of members and BSS usage might not be captured by the member share proxy. Finding monthly data of the actual number of BSS members or using a different proxy could improve the empirical results.

8.3) Unemployment

The coefficient on the level of unemployment is near-zero and insignificant across the board. The result is consistent with the theoretical model's prediction that unemployment's effect on

BSS usage is ambiguous. To further test the ambiguous effect prediction, future tests could divide the unemployment regressor into its constituent parts. The component of unemployment that tends to decrease usage could be represented with unemployment claims, to capture the predicted drop in BSS usage from low income BSS commuters that lose their job. On the other side, the component that tends to increase usage could be represented with the portion of citizens in a low-income range, to capture the predicted spike in BSS usage from an increase in consumers that would demand BSS as a low-cost mode of transportation.

8.4) Housing Price Growth Rate

The coefficient on the growth rate of housing prices is positive across the board. It is significant at the 10% level in Boston, New York City, and Portland for both the regression of TDB and of TD. These results enlighten the incentive model's prediction that the effect of housing prices on usage would be ambiguous. The positive predicted effect suggests that the boost in BSS usage from high-income individuals who might ride for more luxury reasons like health or sustainability concerns outweighs the drop in usage from low-income utilitarian riders being priced out by rising housing prices. The 31.26 coefficient for Boston in the regression of TDB predicts 31.26% growth of TDB for a 1% increase in growth of housing prices (Table 11). The Boston results can be compared to the significant results in New York City and Portland for a city comparison. The 31.26 coefficient on housing prices is larger than the 19.71 and 19.69 coefficients in New York City and Portland, respectively. This predicts that housing prices have more of an effect on BSS usage in Boston than they do in either New York City or Portland.

9. Conclusion

This paper contributes to the study of BSSs and, more generally, urban product adoption. This paper takes a microeconomic foundation and develops an incentive model of urban product adoption. The incentive model proposes a variety of incentives that influence consumers' adoption decisions—incentives that arise from both characteristics of the product as well as characteristics of the urban context of consumption. The incentive model is used to predict the direction of effect for member share, unemployment, and housing prices on the adoption of BSS.

The empirical analysis tests the incentive model's predictions using trip historical data from BSSs in Boston, Los Angeles, New York City, Portland, OR, and Washington DC. The analysis involves time series regressions for the first 36 months of each city's BSS. The econometric specification arises from the mathematical formulation of a city's BSS mode share as an RA's utility maximizing solution to a discrete model. BSS usage is the dependent variable as a proxy for mode share, it is represented by both TDB and TD. The explanatory variable includes the member share in the BSS as well as city-level unemployment and housing prices.

The empirical analysis showed mixed results for the effectiveness of the incentive model at correctly identifying what determines BSS usage. The negative coefficient of member share on BSS usage is contrary to the theory's prediction that BSS usage would increase with member share. This contrary result could be due to a failure to isolate the effect of member share on BSS usage from seasonal fluctuations. This paper is unable to identify a statistically significant effect for unemployment on BSS usage. The significant positive coefficient of housing prices on BSS usage suggests that the boost in BSS usage from high-income individuals that might ride for more luxury reasons like health or sustainability concerns outweighs the drop in usage from low-income utilitarian riders being priced out by rising housing prices. The relative size of housing price coefficients suggests that housing prices have more of an impact on BSS usage in Boston then New York City or Portland.

An important area for future research could be expanding on this paper's empirical analysis. That would include (i) experimenting with different regression specifications to address key issues like seasonality, (ii) bringing in more explanatory variables to capture the product-specific and urban economy determinants of BSS usage, (iii) testing for cointegration to assess the extent to which a long term stable relationship exists between the variables, and (iv) adequately capturing any dynamics in the regression relationships. Informative explanatory variables might include monthly price data, income, and demographic characteristics such as education levels. Improving on the empirical analysis would enable more of the cross-city comparison that this paper briefly touched on in the comparison of housing prices effects in Boston compared to New York City and Portland. Understanding how key determining factors for BSS usage operate differently based on the specific city would be a valuable tool for system operators and city governments that want to incentivize BSS as a sustainable mode of transportation.

Additionally, future research could consider applying the incentive model of urban product adoption to the city-level adoption of other products beyond BSS. The model's framework accounts for the product-specific and key urban economic factors that influence individual adoption decisions, and can therefore be reapplied in the context of different products with relatively minor specification changes.

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