THE EAGLETARIAN

BOSTON COLLEGE ECONOMICS ASSOCIATION

2024

The **Boston College Economics Association** provides students a forum to discuss and explore economics related issues with classmates, professors, and professionals. We accomplish this through small events designed to allow students the opportunities to meet BC faculty as well as larger lectures with professionals in the field. In addition, we publish our annual economics research journal, *The Eagletarian.*

The 2024 Eagletarian

Boston College's Undergraduate Economic Research Journal

Boston College Economics Association 2023-2024 Executive Board:

Dear Reader,

The Boston College Economics Association (BCEA) is pleased to present the 2024 edition of *The Eagletarian*. We received dozens of excellent submissions from across the Boston College student body and believe this publication is only a snapshot of the deep talent and insights of our peers. The essays presented in this issue were chosen by the editorial board after several rounds of reading, discussion, and selection. They represent not only the hard work of our authors, but also the effort we on the editorial board have taken to share with you, our reader, what we found to be the seven most compelling and astute pieces.

In terms of content, we believe this edition will appeal to a wide variety of backgrounds and interests. The works published herein range in content from a comparative study of demonetization in India and an innovative econometric analysis on Airbnb pricing to a policy survey on Semaglutide drug markets.

We would also like to extend our gratitude to several people who were instrumental in our publication process. This publication would not exist without our amazing faculty adviser Professor Matthew Rutledge, who consistently helped us with any problems that arose throughout the year. Moreover, we would like to recognize Charlotte Caine '26 for creating this edition's beautiful cover. Finally, we would like to thank the faculty of the Boston College Economics department for incredible instruction and inspiring their students, our peers, to share their work with the journal and Boston College community.

With regard to BCEA, we would like to specifically thank BCEA President Daniela Lovio for all their great work this year, including their timely assistance to our publication process. Lastly, we would like to thank everyone at Eagle Print for their great work putting the final journal together.

Sincerely,
Jacob Chappelear '24, Braden Kramer '24, Annie Li '25, and Anthony Yang '25

TABLE OF CONTENTS

Analysis of Demonetization in India

From a neoclassical economics and a behavioral economics perspective

Ziling Lyu Vicky

It is my habit to collect some local currency in the countries I travel to, but when I revisited India a few years ago, I found that the currency I brought back from my previous trip was no longer usable and was invalid. Why is this the case? Later, through research, I discovered that ‘demonetization’ has occurred in India.

Demonetization is the act of stripping a currency unit of its status as legal tender. On 8 November 2016, the Indian government announced the abolition of all 500 and 1,000 rupee notes, two currencies that accounted for 86% of the currency in circulation at that time, from the Mahatma Gandhi series (Dasso). Citizens in India were given fifty days to deposit the old specified banknotes (SBN) into their bank accounts, effectively withdrawing these notes from circulation (Nageswaran and Natarajan). The primary goal and objective of demonetization was to clear the system of unaccounted-for cash, address the issue of black money, reduce corruption, and decrease the amount of counterfeit notes in circulation used to finance terrorist activities, which are crucial steps to take for India to attain sustainable high growth (“Demonetisation Essay - Concepts, Merits, Demerits & Effects of Demonetisation in India”).

By measuring nightlight activity, calculating employment surveys to measure economic activity including the informal sector, and collecting transaction data and banking data, the researchers found that areas experiencing greater demonetization experienced a relative decrease in economic activity, lower levels of bank credit growth, and quicker acceptance of alternative digital payment technology (Chodorow-Reich).

The neoclassical economics perspective

The beneficial aspects of demonetization

Since the implementation of demonetization in India, the use of digital transactions and deposits has increased significantly. This shift leads to improved money circulation by enabling money to flow from individual banknotes to banks and financial institutions. For instance, deposits grew by 13.9%, reaching 105 trillion Indian rupees ($1.5 trillion), and the share of electronic transactions in total system transactions climbed to 84.4% (Dasso). In the long run, Microfinance Institutions (MFIs) will increasingly use digital channels for payments and collections, establishing a sustained tendency that propels India toward a successful transition to a cashless economy.

Following demonetization, the Indian economy underwent a formalization process. Previously plagued by serious tax evasion, with black money constituting over 15% of the total currency in circulation in India, the government managed to re-deliver 99% of the circulated currency through demonetization (Belsie). Soumya Kanti Ghosh, Group Chief Economic Advisor of the State Bank of India, asserted that in the years post-demonetization, India's economy witnessed massive formalization, reducing the informal sector's GDP share from 52% to approximately 20%. This transformation is remarkable as the informal sector, which initially constituted over 80% of total employment, has undergone a significant reduction (Nageswaran and Natarajan). Moreover, there is evidence that ongoing efforts to enhance the formalization of the Indian economy would ultimately contribute to an increased potential growth rate, as highlighted in the 2017-2018 national budget documents (Nageswaran and Natarajan).

Furthermore, as the Indian economy progressively embraces electronic systems and makes progress in formalization, Professor Can Erbil, an economics expert and professor of economics at Boston College, agrees that redesigned and newly issued banknotes with enhanced security features may be a feasible solution to the problem of counterfeit currency in India and manage the circulation of money. This is also expected to be coupled with increased utilization of electronic systems, thereby strengthening control over challenges such as black money, illegal activities, and tax evasion.

The adverse consequences of demonetization

During the demonetization process, households in India face significant inconveniences and hardships in their daily life. They are compelled to endure long queues at bank entrances, access unfamiliar electronic systems, and adapt to a series of changes. Additionally, inconvenience and difficulties in communication in India may cause delays in receiving vital information, resulting in financial losses and exacerbating the psychological impact on individuals who cannot exchange their money on time.

Producers and investors also bear the brunt of the negative effects of demonetization. The shortage of new banknotes in circulation forces many individuals to merely rely on coins for their basic daily needs, leading to a reduction in household disposable income. Consequently, the diminished consumption capacity contributes to a decline in demand for goods and services beyond essential items, such as luxury goods. This, in turn, creates a surplus for small and medium-sized enterprises. The excessive supply over demand makes it challenging for firms to earn a profit and places them at risk of bankruptcy.

According to Amartya Lahiri, Faculty Bank Research Professor at the University of British Columbia, the demonetization movement has essentially failed to achieve its intended goals. Due to the widespread acknowledgment that undeclared income is seldom held in cash in India, the objective of eliminating black money by abolishing paper currency faced inherent challenges from the outset (Lahiri). Professor Can Erbil pointed out in an interview with me that the remnants of undisclosed wealth may persist in alternative forms such as jewelry, gold, and other unexpected ways, which is evident that the black money problem cannot be solved simply by restricting the use of two types of banknotes. In addition, Professor Erbil proposed that while only currency denominations of 500 rupees and 100 rupees are limited, “people worked in the black market can still use small denomination currencies for transactions.” Also, in order to ensure the value of the currency, many underground markets may conduct transactions through dollars as its value might be more stable rather than rupees, implying the “estimated low circulation of Indian currency in the black market.” So, it remains to be seen whether demonetization will effectively address the black money problem.

Additionally, demonetization may have a negative impact on the stock market (Lahiri). Studies of digital payments, tax base, and income growth show India's demonetization policy has had little effect. Of course, given the relatively short period of demonetization, conclusions about trends in digital transactions and tax revenue should be viewed as tentative, while the long-term effects will require more time to be verified.

As a result, demonetization of paper currency led to a reduction in output and employment, especially in the informal sector. However, these losses may be temporary rather than permanent. Nevertheless, merely making informal sector economic activity unsustainable without facilitating its transition to the formal sector is detrimental to the economy and society as a whole (Nageswaran and Natarajan). Overall, the demonetization movement appears to have failed to conduct a cost-benefit analysis of public policy measures. It has achieved few of its stated goals and imposed significant costs on the public.

The behavioral economics perspective

Behavioral economics principles used in demonetization in India

Utilizing principles from behavioral economics, the objective of transitioning from cash to electronic payments in India was elusive because it requires a significant change in people's behavior. Before demonetization, 98% of the economy was cash-dependent and less than 5% of households possessed credit cards, so switching habits was crucial (Dasso). Reducing frictional costs and the barriers complicating the required course of action is essential for successful behavior change. In cases where these barriers were unavoidable, the introduction of incentives emerged as a strategy to alleviate frictional costs.

In the process of demonetization, the government created environmental changes by imposing an urgent cash conversion deadline and announcing demonetization, fostering behavioral shifts through these alterations. At the same time, the government has provided incentives such as discounts and tax breaks for digital transactions to reduce frictional costs, facilitating the conversion from cash to digital. Moreover, the government uses the concept of equity within the economic frame, which emphasizes tax fairness, to encourage tax compliance, exemplified by reduced tax rates for specific parties. The government announced a reduction in the tax rate for small companies and individuals with personal income between 250,000 rupees ($3,639) and 500,000 rupees ($7,278), demonstrating social government fairness and incentivizing them to file their taxes. Additionally, the Indian government used the moral frame in behavioral economics to declare that waiting in line at the bank gate to exchange money is a patriotic performance, thereby enhancing public acceptance of this new policy.

Assessing the success of demonetization using behavioral economics concepts

Demonetization cannot be labeled as a successful policy by using experienced utility as a measure since neoclassical economics lacks a clear distinction between 'decision utility' and 'experienced utility.' Decision utility describes the usefulness we perceive and is employed in decision-making, linked to the objectives that economic agents seek to maximize. On the other hand, experienced utility describes the actual consequences of a decision in reality, encompassing the perceived reward or genuine well-being after making a choice (Jayakumar). Neoclassical economics believes that decision utility is sufficient to explain behavior, but this perspective is flawed as decision utility fails to unveil the experienced utility of the decision maker.

The difference between decision utility and experienced utility with respect to decision objects can be significant. The discrepancy between these two concepts of utility leads to the "disturbing possibility that individuals may make incorrect decisions based on systematically overestimating the utility of the consequences of their choices" (Robson and Samuelson). Proponents of demonetization often point to the absence of riots and the patience exhibited by ordinary Indians in long queues as indications of support for the prime minister (Prasad). However, these expressions are mistakenly interpreted as revealing preferences. The support from certain citizens merely reflects decision utility and in no way reveals the true attitude of economic agents (experienced utility) toward the demonetization policy. Consequently, it does not serve as a demonstration of the success of the demonetization effort.

Alternative behavioral economics policies

Alternative behavioral economics policies could offer a comparable impact to the demonetization policy in addressing issues like tax evasion and black money. Compared to demonetization, strategies rooted in behavioral economics, such as nudges, social proof, and framing effect, may also be effective (Jayakumar). Rather than relying on price-based penalties favored by neoclassical economics, these approaches involve behavioral pushes and influence human decision-making based on behavioral economic theories.

Specifically, the concepts of social proof and framing could be pivotal in reducing tax evasion (Jayakumar). Social proof refers to people's tendency to pay attention to the behavior of their peers to guide decision-making and to follow the same behaviors that their peers engage in. Also, framing effects are cognitive biases in which people respond differently to specific choices, depending on how they are presented.

Policymakers might consider adopting the empirical-scientific frame to change individuals' behavior by analyzing the consequences of holding dark money or engaging in tax evasion. The negative framing highlights penalties for such actions, while the positive framing emphasizes the benefits of paying taxes on time and corruption-free in an economy. The utilization of negative framing plays a role in the tendency of personal loss aversion, compelling compliance with policy measures out of fear. Additionally, an efficiency frame can be used by emphasizing that the economic benefits and efficiency of paying taxes outweigh the gains from tax evasion. The Indian government may select a framing method that is suitable for their country's context to address the problem of illegal enterprises and black money.

In my opinion, the government should consider and pay attention to citizens' feelings while seeking quick solutions to issues like black money. The focus should be on better protecting the welfare of citizens, and careful thought should be given to whether outright demonetization will have irreversible adverse effects on households' lives. From the perspective of behavioral economics, demonetization cannot be regarded as a successful move, although from the perspective of neoclassical economics, this move has both positive and negative consequences.

Therefore, I believe that the Indian government needs to take a multi-pronged approach to address the twin challenges of restricting black money and creating social formality. Due to the pervasiveness of the informal economy, both financial and non-financial measures are necessary, the latter may have less impact on people's lives such as the more euphemistic approach of behavioral economics. Also, since reforming and curbing the biggest sources of black money creation - real estate and political corruption - requires long-term efforts, and combating the underground market is also a long-term activity, the rectification cannot just be limited to the simple act of demonetization.

The subsequent combination of neoclassical economics methods based on maximizing individual interests and behavioral economics methods that consider human mood and inner thinking may help the Indian government achieve the ideal state, including but not limited to expanding the tax base, enhancing tax cooperation regulations, and using nudges to get people to pay their taxes on time and use digital transactions.

In conclusion, despite the many drawbacks of demonetization, with the subsequent multi-dimensional measures taken by the government, demonetization may be viewed as successful for the country's long-term development. This success lies in the formalization and digitization it brings, in line with the broader goals of national development.

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Determinants of Airbnb Prices: Considering Amenities and Room Types

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Abstract: Many past studies on Airbnb using the inside Airbnb data have investigated determinants of price using hedonic ordinary least squares (OLS) regression models, but few have taken to looking at specific amenities shown in the data set or testing the amenities suggested by the Airbnb website. We aimed to create a regression model building off of the findings of other studies with the inclusion of dummy variables to encode each amenity separately and to cover concerns of heteroskedasticity through the use of generalized least squares (GLS) and bootstrapping standard errors. Our results show that amenities do vary with listing types, and selected amenities are statistically significant, however results are still partially inconclusive.

Keywords: Airbnb; pricing; amenities; property type

We thank Professor Christopher Maxwell for valuable instructions on our drafts.

1 Data

Our data was taken from insideAirbnb.com which is a massive data-scraping project for the primary purpose of machine learning. The data is scraped directly from the Airbnb website every three months, specifically in March, July, September, and December. We were able to obtain data reaching back to September 2021.

This data set includes numerical and textual data. While the numerical data has been studied extensively, we are focusing first on creating a model that controls for numerical variables while studying the textual data, specifically amenities. Listings include the current and future listings available on the website's booking calendar. The booking calendar is given a separate data set listing each day for each listing in the sample which also records all reviews, with the rating and date for every observation. As to the price data's accuracy, this is presupposed that prices in the data set refer to Airbnb's listing prices, not necessarily the final transaction prices and our price variable does not take the different listing prices which occur on different days, but an average of these prices. Although the calendar provides more specific (day by day) prices, we chose to use the prices given in the broader listings data set as these are far easier to work with and the daily prices from the calendar tended not to vary often (remaining at one price), described by the price variable in the listing data set. This is addressed in the final section on data improvements. **Table 2** shows the average prices for each listing type, separated by time. Here we can see some evidence of seasonality but no regular pattern. This may be to the removal of COVID policy and the re-opening of travel, which lends to further study. It seems that the prices of homes versus apartments have separated as time passes.

Table 1 shows the distributions of listings over time, sorted by property type. The time periods used are denoted as variables from 1 through 6, where 8 Airbnb lists 66 different property types ranging from castles to city apartments ($RmTp$). In our treatment of the data, some obscure rental types were dropped and we used the broader categories of entire units, or private rooms and apartments or non-apartments. The other difference in listings is whether they are rented out as a whole unit or a private room in a house (*Entire*) As one would expect, the majority of apartments are rented out as a whole unit and are generally located closer to the city center of Boston as can be seen in **Table16**. Most of the houses are farther away from the city center and are the primary renters of single rooms. This is all verifiable by looking at conditional sample means. This basic tabulation does not lend to analysis other than the rise in listings over time.

Tables 3-6 shows the numerical frequencies of amenities within the data. We suspect that the provided amenities affect the prices of listings. With the data, the names of the amenities were largely standardized, making analysis simple, but there are examples of inconsistency which could produce small discrepancies. Displayed in the tables are the most common unique amenities from the data including air conditioning, free parking, heating, a Jacuzzi, a kitchen, a pool, Laundry capabilities, wifi, and a workspace. Airbnb provides a list of the most demanded amenities [1], giving their own hypothesis on the top amenities demanded. We chose these to test as a benchmark for amenities but included more amenities to test against Airbnb's suggested variables.

Latitude and Longitudinal data, displayed in **Table 7** are in our regression to measure distance variables from the listing to various points of interest. The distance from the listing to the city center (*distCenter*) is the most important explanatory variable in terms of location and can be seen to be included in most studies concerning both Airbnb and hotel analysis. We examine the distance from the listing to the average location of other listings (*distList*) and the distance from the airport (*distAirport*) as per the suggestion of prior studies (Augusto Voltes-Dorta and Agustín Sánchez-Medina (2020)). When looking at the different distances, we saw that the correlation between these variables was very high, and when tested under regressions, it resulted in VIFs over 5, the accepted threshold for multicollinearity, so listing distance and the airport distance was excluded from all regressions.

We include a variable using neighborhood within our regression models to control for location effects. This is an important aspect for further analysis, as each coefficient is dependent on neighborhood and requires further exploration. To account for this variation, we included an encoded variable which allows us to control for the Neighborhood (*Nbhd*). It takes on a value ranging from 1 to n where n is the total number of neighborhoods in the sample. This means that although the effect is partially controlled within our regression models, it is not interpretable.

Another noteworthy variable is license, which takes on 3 values in Boston[2]: missing, policy number, or an exemption. These values vary on a state-by-state basis which is accounted for in the multi-city regression displayed in **Table 17**. In our case with Boston, the license is shown on the Airbnb website. If a policy number is displayed, the unit is registered with the government for rentals under 30 days and this data is reported to the government. About 75% of the non-missing values fall under this type. One discovered flaw with this data is the way it treats the license, as there is no correlation between having a license and being listed for greater or less than 30 days. This topic is discussed in the data improvement section.

In the final section of the paper, we include regression analysis involving multiple cities: Austin, Chicago, Denver, Nashville, New York City and Los Angeles (again **Table 17**). This data is helpful, but

[1] See https://www.airbnb.com/resources/hosting-homes/a/the-best-amenities-to-offer-right-now-203

[2] Listings function differently on a city by city basis, so when including multiple cities, this effect is ignored

reveals some repercussions on the scope of our analysis. First, the inside Airbnb data sets only include large cities. More comprehensive study could be done with data scraped from all Airbnb properties and one could theoretically create a dataset which is the population of listings. There may be bias within our data towards the effect of large cities, but in selecting these cities we determined that the selected cities were sufficiently diverse to cover different aspects of large cities. Second is the factor of the distance ranges over which data is collected. There are listings in the data which fall outside city limits in every sample. This is true of both the added cities and the Boston data. For the LA sample, the data was trimmed in the sense that we removed a selection of the data which was north of a certain point since it would have skewed the variable for the distance from the city's center which is again the constraint of limited graphical analysis.

2 Methodology

To determine the basic drivers for Airbnb listings, we employed various hedonic ordinary least squares (OLS) price regressions. Adjusted R squared, F-tests and t-statistics were used as benchmarks for model preformance, and all indicators of statistical significance are measured at the 5 percent level. Robust standard errors are used to minimize the presence of heteroskedasticity. This is done by allowing the variance matrix to have different values along its diagonal and weighting observations based on their calculated variances, which generally increases the standard error of a given variable. Post-regression variance inflation factors (VIF) were used in all models to detect the presence of multicollinearity. The VIFs estimate multicollinearity by observing the R^2 of each variable on the other remaining independent variables, taking advantage of the way R^2 measures the extent of the data explained by the model. We removed variables with VIFs over 5 unless there was other reason to include them in the data, as is accepted as the standard. We suspect that heteroskedasticity would be one of the primary difficulties in estimating this kind of model, as certain listing prices may produce more variance in quality. All models were regressed on the log of price, assuming a non-linear fit which has been shown by other studies. In doing so, all coefficients represent the percent change in the regressions in which the log of prices is used.

In determining which variables from the listings data sets are most useful, we consulted variable selection algorithm package vselect and stepwise from the STATA packages and intuitions garnered from prior studies(Voltes-Dorta and Sánchez-Medina, 2020). We ran several combinations, maximizing the aforementioned statistics of R^2, and F-Stats. From the algorithmic selection processes we were convinced to omit certain variables, especially those describing the host. Although certain regression models showed statistics about the host to be significant with regards to t-stats, when using the selection algorithms in union with independent adjusted R^2 analysis, we determined that these were not significant predictors of price and were all omitted except of the number of listings the host has (*HostListCount*). Through the process of regressing different variables, many other potential variables were omitted from the model for being inefficient or insignificant when considering the adjusted R^2, which takes the number of variables into account when looking at model efficiency.

We first used one regression with complex panel data analysis as seen in **Table 9**, including all the variables listed above with no data subsets to create separate regression based on the type of listing, instead encoding the listing type variables as dummy variables (*Entire*, *Apt*). Since we have data on the collection time of the listings, we can use this to encode the date (*Date*) as a linear variable, allowing us to account for time as an influence on listing price. This allows for all variables to be treated all at once in linearly, giving us a general picture so that we may proceed carefully to more complex analysis. The OLS specification is shown below:

$$\begin{aligned}\ln(price) = {} & \beta_0 + \beta_1 Entire + \beta_2 Apt + \beta_3 Nbhd + \beta_4 Date + \beta_5 accommodates + \beta_6 bedrooms + \beta_7 beds \\ & + \beta_8 availability\_30 + \beta_9 HostListCount + \beta_{10} BathNum + \beta_{11} Lc + \beta_{12} distCenter \\ & + \beta_{13} VrNum + \beta_{14} Rating + \beta_{15} minimum\_nights + \beta_{16} AmNum + u\end{aligned}$$

Where u represents error and β_n represents the estimated percentage effect on each variable. .

After this regression, we move to sub-sampling. This approach involves dividing the OLS model regression into different sub-samples based on the type of listing. This approach was chosen due to the suspected intuitive relationship between the perceived value of certain amenities and the property listing types. This has the additional effect of accounting for the problem of heteroscedasticity within the bounds of different listing types. These next models used separately sub-sampled regressions, selecting data partitions based on the type of listing (Not Entire Listing, Entire Listing, Not Apartment, Apartment) as is seen in Table 9, with the advantage of this analysis being able to see different effects of our selected independent variables instead of a mass of interaction terms in one total regression. These regressions take the same form as those above simply with different selections of data.

To treat heteroskedasticity in the data, we use a regression analysis with bootstrapped standard errors with data subsets of size 50, which only changes our t-statistics and thus levels of statistical significance. Bootstrapping is a form of standard error resampling which adjusts the standard errors by creating random sub-samples of the data (in our 50 iterations) with replacement and observing the variation in coefficients.

We employed another method of accounting for the presence of heteroskedasticity - the generalized least squares regression (GLS). GLS is a form of weighted least squares where observations are weighted based on a prediction made about the individual observation's error terms. These estimates are generated by regressing the predicted values from the first stage regression on the independent or right-hand side variables. Then, taking the residuals of the second-stage regression, we use those residuals in a third-stage weighted least squares regression where the weights are described by

$$W = \frac{1}{\hat{u}^2}$$

Where $\hat{u}^2$ is the residuals of the second-stage regression, which comes from the original regression shown in **Table 10**. This allows us to go further than the correction made by the previously employed robust standard errors, and modify the coefficient estimates based on the variance of individual observations. This is different from the robust standard errors as the changing of standard errors only involves changing measures of statistical significance, not the model itself.

After using these two models separately, we experimented with a new method of heteroskedastic analysis, which we will call double internal variance adjustment (DIVA). DIVA involves using bootstrapping and GLS in tandem, which allows for the treatment of the variance twice (as is suggested in the name) as heteroskedasticity is first modified by accounting for individual error variances within the model (GLS), and then again within the scope of the data (bootstrapping). There is some literature discussing this topic (Mantobaye Moundigbaye, Clarisse Messemer, Richard W. Parks and W. Robert Reed, 2020-4) & (Lawrence H. Moulton and Scott L. Zeger, 1991) but the method of employing both methods simultaneously with DIVA seems to be unexplored.

We display two versions of this regression model, one where bootstraps are calculated first and GLS is run afterward (Table 14), and one which first performs GLS to generate the model and performs the resampling afterward (Table 13). The results of such will be discussed later, but from a brief overview of the topic, it would be reasonable to assume that the first method (GLS first) is more useful since one takes advantage of the change in the model when performing the bootstraps on the standard error which is generated out of the creation of the model. More study is required on this matter.

Finally, we ran a negative binomial regression on price rather than the log of price since price has only non-negative integer values. This should produce similar results as the integer values of prices are arbitrary. We also ran a Poisson model when first examining the data, however, this proved to be a far inferior technique as the data does not fit the Poisson distribution in which the mean and variance are the same. We can see based on the value and t-statistic of alpha (which if zero, indicates the presence of a Poisson distribution) is significantly different from zero. Based on this we can conclude that the Poisson model is not fit for use in this instance.

From here, we move on to our amenities regressions looking only at the effects of amenities, regardless of property typing or location. These are done in the same fashion as above, proceeding from standard hedonic OLS models to bootstrapped standard errors, generalized least squares models, and DIVA.

3 Results and Discussion

When looking at the undifferentiated OLS model, it appears that every variable is significant. However, when moving to models with different data subsets, more insight is given to specific amenities. Before looking at each model in depth, it is worth noting that one of the largest reasons for variation in the subsets titles "Not Apartment" is the number of different listings in terms of property types (*property_type*). In order to generate these regressions, we had to create a binary distinction between property types. We chose apartments and not apartments in hopes that it would best capture the difference between an apartment and a house resting on the idea that there was little in between, but the variation in types of houses is difficult to measure. It is a drawback of these models.

When moving to individual property type subsets, we can see that the models for the apartments prove to explain more of the data. This is likely due to the larger amount of variation of property type within the section of houses. We suspect that this has a lot to do with location, which is the best way to expand our model. When aggregating the data, we put many different property types such as condos, townhouses, villas, lofts, and the ambiguous "rental unit" into the housing category as compared to the narrower, not apartment category. This is simply a repercussion of the data itself, there are not enough unique observations within these subsets of our housing variable to regress separately.

As would be expected, the bootstrap model is quite similar to the base model, in that measures of statistical significance change, but the model does not.[3] This ends up having almost no effect, as few coefficients move to different levels of statistical significance with the resulting changes in standard error. Losses in levels of statistical significance are seen only in AC and Pool.

As would be expected, the bootstrap model is quite similar to the base model, in that measures of statistical significance change, but the model does not. This ends up having almost no effect, as few coefficients move to different levels of statistical significance with the resulting changes in standard error.

[3]When comparing model effectiveness, all the following models will be compared with the base model described in **Table 10**.

Losses in levels of statistical significance are seen only in AC and Pool.

The GLS model has a worse performance than the basic model in terms of the Adjusted R^2 and F-stats however. We deem this to be a necessary loss in explanatory power to account for correlated error in the model. Here we do see some more drastic changes in the coefficients of amenities and their respective statistical significance, with changes in levels of statistical significance across every single variable.

When employing DIVA, we will only consider **Table 13** due to the reasons reasons discussed above[4], but include **Table 14**. This results in changes in our results when compared to the base models, but only to the extent that t-stats are lower. This is expected since the only difference between **Table 12** and **Table 13** is the inclusion of bootstrapping which only changes standard errors between the two, so their performance is also the same.

When looking at these classifications of similar models, it is clear based on the R^2 and other goodness of fit metrics that generalized least squares is the preferred model, with the effectiveness of the DIVA regression left ambiguous. The t-stats shown on many of the models lead us to believe that the effects of amenities are smaller than expected or otherwise shown by the subset less model.

The negative binomial regression model presents a largely different interpretation of the model as few coefficients retain the same levels of significance or even predicted effects. However, when measuring this model's Pseudo R^2, it can be assumed that since it performs vastly worse that the model serves no explanatory usage. The negative binomial is not suited to this data. This is likely since price is not truly a count variable but simply takes the form of one due to Airbnb's listed prices.

Another sub-sample that was run was between the two halves of the distance to city center, separated at the median value of this distance. This was run in the hopes of capturing the effect of distance from the city center on various amenities. This model employs only basic OLS, but one can see the effect. Most of the non-amenity control variables remain the same, but there are differences in amenity effect based on distance which are roughly conveyed here. Notable among these are the parking variables (*FrPark* and *PPark*) although free parking matters more than paid parking when closer to the city center, as would be expected. Additionally, a grill is far more significant when closer to the city center. Again, these must be taken as general indications of significance which ought to be further studied with more precise analysis.

Lastly is our data across cities. The results are not as consistent as we had hoped, which lends itself to further study. Again, this is a fairly simple model which just looks to cross-reference our idea

[4] GLS first, Bootstrapping Second

across cities, but this produces wildly different results. For example in Austin and Nashville wifi is not significant with regards to price, but is in all the other cities. If the amenities in question vary to this extent across cities, these differences may not however be exaggerated if one were to subdivide into listing types.

4 Main Findings

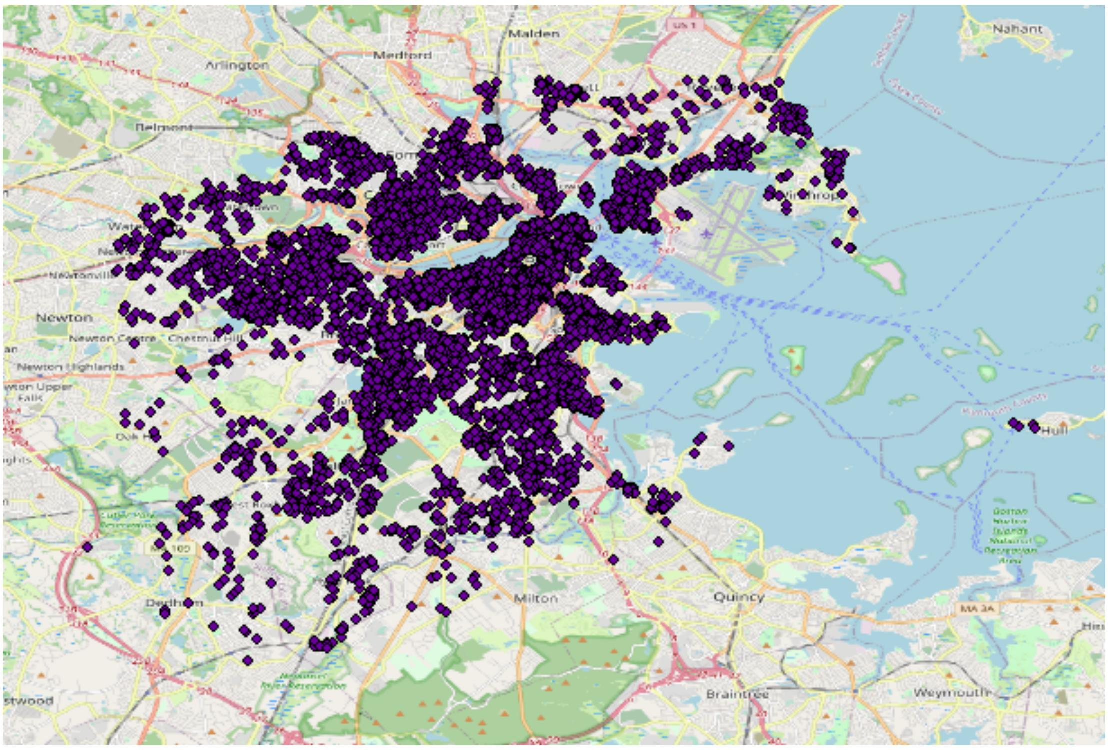
With regards to the primary regression models, it appears that our results are in line with other studies on the matter, that our selected independent variables are all significant, with special emphasis on the property type, shared room, and distance from city center. This model produces results similar to other studies, with an R^2 ranging between .5 and .7.

When examining the various included amenities, we can see that in the simple amenities-only regressions that the number of amenities is far more significant for apartments than houses. When we include other categories, this effect disappears and the number of amenities is determined to be statistically insignificant. Overall, each individual amenity is more significant when considering listings which are apartments. When examining the categories suggested by Airbnb on their list (pool, wifi, kitchen, free or paid parking, jacuzzi, washer/dryer, air conditioning, self-check-in, a workspace and pets allowed) only kitchen, free or paid parking and TV share any measurable correlation to the price of the respective booking. These should be the main concerns of Airbnb hosts.

Within the different data subdivisions, it is worth noting that kitchens and grills in apartments have no measurable effect on price while they are highly significant in non-apartments. Apartments tend to have higher prices when listed with a large number of amenities, but houses tend to rely on specific amenities rather than a multitude.

5 Possible Model Improvements

One possible improvement with regard to the data is the further implementation of latitude and longitudinal data. We were able to use this data to calculate the estimated effects of the distance from the Airbnb to the city center, but any further investigation of proximity would require the usage of GIS mapping software. It would be possible to examine the effect of distance from public transportation, tourist attractions, and major shopping districts using these methods, given more time to learn the software. As proof of concept, we were able to generate a map of all the listings in Boston through ARCMaps, with background maps sourced from openstreetmap.com, a cutting-edge open-source collaborative map of the world. Below is the limited work we were able to do with this software.



Another possible implementation of this data would be regarding government-reported data. In states like New York, any listings under 30 days are required to be publicly documented by the local government. If we had access to this data, we could cross check the transaction prices and produce a more interesting analysis of prices, as transaction price may differ from listed price. There may be merits to this sort of difference analysis with respect to ratings as well, providing further usefulness to the breadth of data on the specific reviews. Reviews would serve as an alternative to price as the independent variable, especially given the idea that prices may have a significant effect on reviews. We chose not to take this approach due to the complexity of analyzing the reviews. In order to make best use of this data, it would have been necessary, or at least helpful to look at the text written by users, which is a task for machine learning, not econometrics analysis.

We were only able to access six periods worth of data, but it was stated that there were earlier archived scrapes available at a price. This would allow for more sophisticated panel data and time series analysis., allowing for time to be a more reliable dependent variable. It is also worth noting that since the calendar data is present, one could create a more detailed picture of the data using dates for every day in the sample, although this increases the size of the data set drastically. This data set still has much untapped potential.

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Appendix

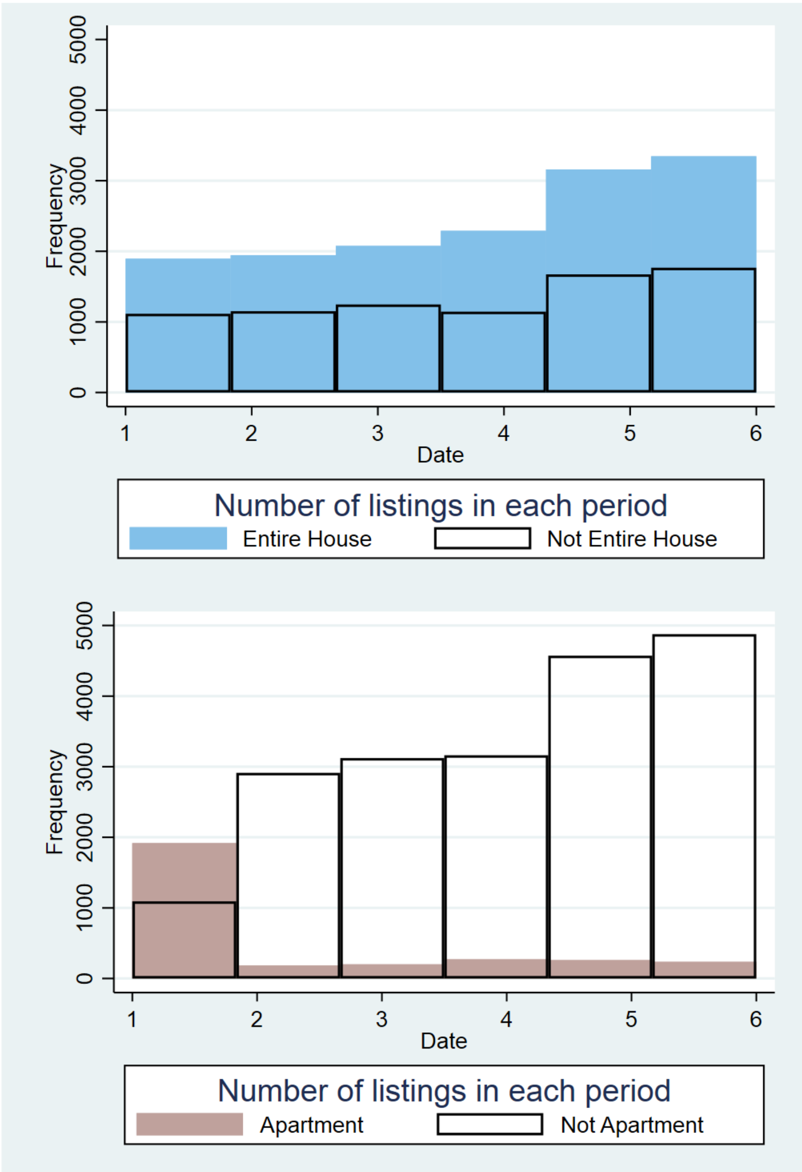

Figure 1: Frequency of Listings

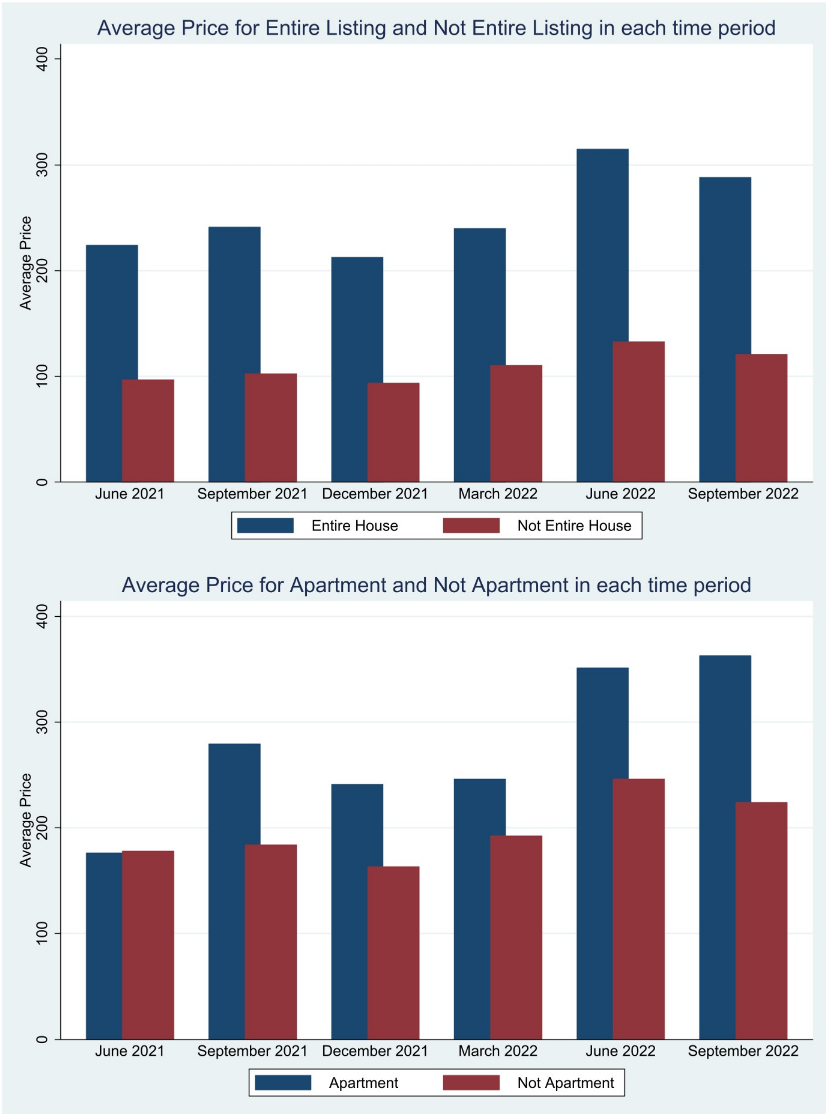

Figure 2: Average Listing Price

Table 1: Frequency of amenities in each period (Part 1)

	Ac	FrPark	Heating	Jacuzzi	Kitchen	Pool	Washer
0							
June 2021	18.57	58.17	7.973	99.53	9.767	92.52	28.50
September 2021	18.18	58.99	10.11	99.58	10.56	92.54	29.16
December 2021	20.16	60.16	12.16	99.64	10.32	91.21	32.29
March 2022	22.62	61.22	17.58	99.59	10.39	88.88	33.74
June 2022	27.35	57.44	16.97	99.65	10.84	92.26	38.36
September 2022	33.95	59.23	18.38	99.67	10.23	93.45	39.44
1							
June 2021	81.43	41.83	92.03	0.465	90.23	7.475	71.50
September 2021	81.82	41.01	89.89	0.420	89.44	7.459	70.84
December 2021	79.84	39.84	87.84	0.361	89.68	8.787	67.71
March 2022	77.38	38.78	82.42	0.408	89.61	11.12	66.26
June 2022	72.65	42.56	83.03	0.352	89.16	7.738	61.64
September 2022	66.05	40.77	81.62	0.332	89.77	6.551	60.56

Table 2: Frequency of amenities in each period (Part 2)

	Wifi	Workspace	TV	Luggage	PPark	Grill
0						
June 2021	1.894	25.75	18.50	72.26	80.27	90.90
September 2021	1.840	30.84	18.47	73.88	80.63	89.96
December 2021	2.588	32.44	16.82	75.32	80.41	89.56
March 2022	2.766	31.32	16.39	74.38	78.49	88.01
June 2022	3.642	65.69	17.94	73.14	77.30	86.01
September 2022	5.241	58.70	17.03	73.46	75.64	87.02
1						
June 2021	98.11	74.25	81.50	27.74	19.73	9.103
September 2021	98.16	69.16	81.53	26.12	19.37	10.04
December 2021	97.41	67.56	83.18	24.68	19.59	10.44
March 2022	97.23	68.68	83.61	25.62	21.51	11.99
June 2022	96.36	34.31	82.06	26.86	22.70	13.99
September 2022	94.76	41.30	82.97	26.54	24.36	12.98

Table 3: Frequency of amenities for Not Entire Listing v.s Entire Listing (Part 1)

	Ac	FrPark	Heating	Jacuzzi	Kitchen	Pool	Washer
0							
Not Entire House	26.18	46.97	11.64	99.64	22.57	96.94	42.57
Entire House	23.83	65.80	16.16	99.61	3.671	89.18	30.01
1							
Not Entire House	73.82	53.03	88.36	0.358	77.43	3.061	57.43
Entire House	76.17	34.20	83.84	0.394	96.33	10.82	69.99

Table 4: Frequency of amenities Not Entire Listing v.s Entire Listing (Part 2)

	Wifi	Workspace	TV	Luggage	PPark	Grill
0						
Not Entire House	3.432	44.41	37.24	71.16	85.11	91.14
Entire House	3.134	43.93	6.607	75.10	74.71	86.64
1						
Not Entire House	96.57	55.59	62.76	28.84	14.89	8.863
Entire House	96.87	56.07	93.39	24.90	25.29	13.36

Table 5: Frequency of amenities for Not Apartment v.s Apartment (Part 1)

	Ac	FrPark	Heating	Jacuzzi	Kitchen	Pool	Washer
0							
Not Apartment	22.66	55.75	12.93	99.58	11.58	94.23	36.44
Apartment	37.59	80.72	25.02	99.84	2.671	77.20	21.86
1							
Not Apartment	77.34	44.25	87.07	0.415	88.42	5.769	63.56
Apartment	62.41	19.28	74.98	0.163	97.33	22.80	78.14

Table 6: Frequency of amenities Not Apartment v.s Apartment (Part 2)

	Wifi	Workspace	TV	Luggage	PPark	Grill
0						
Not Apartment	3.612	44.48	18.65	71.84	78.56	88.32
Apartment	0.847	41.66	10	85.70	77.36	87.69
1						
Not Apartment	96.39	55.52	81.35	28.16	21.44	11.68
Apartment	99.15	58.34	90	14.30	22.64	12.31

Table 7: Correlation between bedrooms, beds, accommodates

Variables	bedrooms	beds	accommodates
bedrooms	1.000		
beds	0.827	1.000	
accommodates	0.810	0.844	1.000

Table 8: Sample means of the chosen variables

	(1) June 2021 mean	(2) September 2021 mean	(3) December 2021 mean	(4) March 2022 mean	(5) June 2022 mean	(6) September 2022 mean
price	177.1	189.8	168.2	196.9	252.0	230.5
Entire	0.630	0.628	0.625	0.667	0.654	0.654
Apt	0.637	0.0594	0.0602	0.0792	0.0538	0.0461
Nbhd	11.79	11.84	11.92	11.86	10.31	10.19
accommodates	3.084	3.081	3.054	3.200	3.279	3.239
bedrooms	1.457	1.465	1.471	1.534	1.581	1.582
beds	1.662	1.656	1.740	1.776	1.840	1.844
availability_30	10.01	8.515	12.69	9.299	7.363	7.542
HostListCount	20.71	23.60	32.29	27.94	49.32	62.66
BathNum	1.272	1.301	1.310	1.286	1.287	1.284
Lc	0.541	0.544	0.550	0.557	0.459	0.458
distCenter	4.130	4.152	4.134	4.105	4.544	4.477
VrNum	5.389	5.431	4.913	5.160	2.183	2.186
Rating	4.650	4.659	4.664	4.670	4.691	4.688
minimum_nights	39.71	39.45	39.24	34.37	28.99	27.66
AmNum	27.46	27.47	27.67	28.35	28.94	29.48
Observations	3010	3097	3323	3435	4833	5114

Table 9: Airbnb lising price regressed on listing's characteristics

	(1)
	b/t
Entire	0.561^{***}
	(53.25)
Apt	0.0397^{**}
	(2.79)
Date	0.0383^{***}
	(12.23)
Nbhd	-0.00464^{***}
	(-8.56)
accommodates	0.0800^{***}
	(22.31)
bedrooms	0.171^{***}
	(20.63)
beds	-0.0375^{***}
	(-6.69)
availability_30	0.00999^{***}
	(24.81)
HostListCount	0.000952^{***}
	(9.06)
BathNum	0.0654^{***}
	(8.60)
Lc	0.151^{***}
	(15.32)
distCenter	-0.0616^{***}
	(-42.30)
VrNum	-0.0255^{***}
	(-11.22)
Rating	0.0611^{***}
	(7.77)
minimum_nights	-0.00129^{***}
	(-10.64)
AmNum	0.00330^{***}
	(8.87)
Constant	3.839^{***}
	(88.90)
Observations	14722
R-squared	0.627

Adj. R-squared	0.627
F-stat	1545.4

Source: Inside Airbnb

Table 10: Airbnb lising price regressed on listing's characteristics by property type

	(1) Not Entire Listing b/t	(2) Entire Listing b/t	(3) Not Apartment b/t	(4) Apartment b/t
Apt	-0.0393	0.0879***		
	(-1.64)	(6.12)		
Date	0.0310***	0.0425***	0.0269***	0.0631***
	(6.10)	(11.05)	(7.48)	(7.06)
Nbhd	-0.00583***	-0.00210**	-0.00477***	-0.00518***
	(-7.19)	(-3.29)	(-8.66)	(-3.78)
accommodates	0.147***	0.0373***	0.0716***	0.0535***
	(9.37)	(9.03)	(16.47)	(4.16)
bedrooms	0.149***	0.170***	0.186***	0.191***
	(6.18)	(18.63)	(18.79)	(7.33)
beds	-0.0555**	-0.0276***	-0.0299***	-0.0158
	(-2.96)	(-4.64)	(-4.93)	(-0.86)
availability_30	0.0108***	0.00882***	0.00942***	0.00439***
	(16.72)	(14.70)	(19.25)	(4.33)
HostListCount	-0.000786**	0.000916***	0.000709***	0.000116
	(-2.70)	(11.14)	(9.03)	(0.22)
BathNum	-0.0696***	0.261***	0.0555***	0.153***
	(-9.06)	(22.74)	(6.91)	(6.73)
Lc	0.103***	0.126***	0.118***	0.313***
	(6.26)	(11.11)	(10.37)	(8.79)
distCenter	-0.0426***	-0.0425***	-0.0455***	-0.0507***
	(-16.75)	(-20.72)	(-26.29)	(-10.32)
VrNum	-0.0277***	-0.0157***	-0.0256***	-0.00111
	(-8.17)	(-6.15)	(-10.56)	(-0.22)
Rating	0.0441***	0.0594***	0.0667***	0.0289
	(4.24)	(6.48)	(8.68)	(1.45)
minimum_nights	-0.00212***	-0.000226	-0.00125***	0.00241***
	(-9.99)	(-1.27)	(-6.15)	(4.88)
AmNum	0.000639	0.000983	0.000694	0.00573***
	(0.82)	(1.75)	(1.36)	(3.69)
Am_Wifi	-0.0787*	0.0140	-0.0575**	0.0867
	(-2.15)	(0.59)	(-2.77)	(0.57)
Am_Heating	-0.0985***	-0.0162	-0.0502***	-0.00609

	(-5.27)	(-1.19)	(-4.24)	(-0.15)
Am_Ac	-0.00389	-0.0488***	-0.0155	-0.137***
	(-0.26)	(-4.05)	(-1.53)	(-4.75)
Am_Pool	0.159***	0.182***	0.253***	0.169***
	(4.27)	(8.32)	(12.70)	(3.47)
Am_Kitchen	-0.208***	0.163***	-0.189***	-0.00817
	(-12.33)	(8.40)	(-13.10)	(-0.16)
Am_FrPark	-0.0675***	-0.0854***	-0.0819***	-0.135***
	(-4.47)	(-6.89)	(-7.99)	(-3.87)
Am_Jacuzzi	0.391***	0.0949*	0.261***	0.318***
	(5.95)	(2.21)	(6.08)	(4.68)
Am_Washer	0.0328*	0.0120	0.0345***	0.0158
	(2.53)	(1.04)	(3.61)	(0.71)
Am_Workspace	-0.0131	0.0142	-0.0130	-0.0376
	(-0.95)	(1.28)	(-1.34)	(-1.44)
Am_TV	0.160***	0.145***	0.170***	0.199***
	(11.01)	(7.99)	(14.49)	(5.69)
Am_Luggage	0.0605***	0.0121	0.0394***	0.00941
	(3.70)	(1.11)	(3.88)	(0.33)
Am_PPark	0.173***	0.0999***	0.149***	0.0432
	(6.40)	(8.36)	(11.08)	(1.55)
Am_Grill	0.0243	0.0720***	0.0917***	0.0563
	(1.09)	(4.83)	(6.73)	(1.29)
Entire			0.544***	0.648***
			(46.94)	(18.52)
Constant	4.290***	3.948***	4.008***	3.352***
	(50.23)	(65.55)	(74.01)	(17.17)
Observations	6124	8598	13193	1529
R-squared	0.435	0.519	0.644	0.787
Adj. R-squared	0.433	0.518	0.643	0.783
F-stat	167.5	355.3	1021.0	281.8

Source: Inside Airbnb

Table 11: Airbnb lising price regressed on listing's characteristics by property type (Boostrap)

	(1) Not Entire Listing b/t	(2) Entire Listing b/t	(3) Not Apartment b/t	(4) Apartment b/t
Apt	-0.0393	0.0879^{***}		
	(-1.83)	(6.78)		
Date	0.0310^{***}	0.0425^{***}	0.0269^{***}	0.0631^{***}
	(5.63)	(10.20)	(7.37)	(7.82)
Nbhd	-0.00583^{***}	-0.00210^{**}	-0.00477^{***}	-0.00518^{***}
	(-7.64)	(-2.97)	(-7.61)	(-4.01)
accommodates	0.147^{***}	0.0373^{***}	0.0716^{***}	0.0535^{***}
	(9.22)	(8.59)	(13.96)	(4.41)
bedrooms	0.149^{***}	0.170^{***}	0.186^{***}	0.191^{***}
	(5.88)	(18.04)	(19.42)	(7.58)
beds	-0.0555^{**}	-0.0276^{***}	-0.0299^{***}	-0.0158
	(-2.72)	(-4.22)	(-5.35)	(-0.90)
availability_30	0.0108^{***}	0.00882^{***}	0.00942^{***}	0.00439^{***}
	(16.26)	(12.54)	(19.73)	(4.87)
HostListCount	-0.000786^{*}	0.000916^{***}	0.000709^{***}	0.000116
	(-2.55)	(9.96)	(9.70)	(0.21)
BathNum	-0.0696^{***}	0.261^{***}	0.0555^{***}	0.153^{***}
	(-6.85)	(20.44)	(6.52)	(6.91)
Lc	0.103^{***}	0.126^{***}	0.118^{***}	0.313^{***}
	(6.97)	(11.72)	(8.60)	(8.59)
distCenter	-0.0426^{***}	-0.0425^{***}	-0.0455^{***}	-0.0507^{***}
	(-17.06)	(-18.65)	(-28.60)	(-10.20)
VrNum	-0.0277^{***}	-0.0157^{***}	-0.0256^{***}	-0.00111
	(-7.93)	(-7.19)	(-11.45)	(-0.26)
Rating	0.0441^{***}	0.0594^{***}	0.0667^{***}	0.0289
	(4.92)	(9.11)	(7.54)	(1.49)
minimum_nights	-0.00212^{***}	-0.000226	-0.00125^{***}	0.00241^{***}
	(-9.09)	(-1.17)	(-5.88)	(4.79)
AmNum	0.000639	0.000983	0.000694	0.00573^{***}
	(0.83)	(1.86)	(1.63)	(3.63)
Am_Wifi	-0.0787^{*}	0.0140	-0.0575^{**}	0.0867
	(-2.10)	(0.76)	(-2.61)	(0.52)
Am_Heating	-0.0985^{***}	-0.0162	-0.0502^{***}	-0.00609

	(-4.93)	(-1.30)	(-3.93)	(-0.16)
Am_Ac	-0.00389	-0.0488***	-0.0155	-0.137***
	(-0.29)	(-4.49)	(-1.30)	(-4.74)
Am_Pool	0.159***	0.182***	0.253***	0.169**
	(3.97)	(6.44)	(15.48)	(3.24)
Am_Kitchen	-0.208***	0.163***	-0.189***	-0.00817
	(-13.94)	(8.03)	(-12.11)	(-0.17)
Am_FrPark	-0.0675***	-0.0854***	-0.0819***	-0.135***
	(-4.92)	(-7.42)	(-7.59)	(-4.09)
Am_Jacuzzi	0.391***	0.0949*	0.261***	0.318***
	(5.10)	(2.34)	(4.94)	(4.13)
Am_Washer	0.0328*	0.0120	0.0345***	0.0158
	(2.57)	(1.03)	(4.00)	(0.80)
Am_Workspace	-0.0131	0.0142	-0.0130	-0.0376
	(-1.06)	(1.20)	(-1.22)	(-1.59)
Am_TV	0.160***	0.145***	0.170***	0.199***
	(10.89)	(7.70)	(14.92)	(5.83)
Am_Luggage	0.0605***	0.0121	0.0394***	0.00941
	(3.98)	(1.05)	(4.05)	(0.29)
Am_PPark	0.173***	0.0999***	0.149***	0.0432
	(6.01)	(9.74)	(13.17)	(1.73)
Am_Grill	0.0243	0.0720***	0.0917***	0.0563
	(1.32)	(5.26)	(6.40)	(1.08)
Entire			0.544***	0.648***
			(45.28)	(21.53)
Constant	4.290***	3.948***	4.008***	3.352***
	(47.85)	(74.58)	(64.20)	(17.62)
Observations	6124	8598	13193	1529
R-squared	0.435	0.519	0.644	0.787
Adj. R-squared	0.433	0.518	0.643	0.783

Source: Inside Airbnb

Table 12: Airbnb lising price regressed on listing's characteristics by property type (GLS)

	(1) Not Entire Listing b/t	(2) Entire Listing b/t	(3) Not Apartment b/t	(4) Apartment b/t
Apt	-0.284**	0.0546		
	(-3.22)	(1.62)		
Nbhd	-0.00665***	-0.00305**	-0.00562***	-0.00614***
	(-4.45)	(-2.94)	(-6.01)	(-4.03)
accommodates	0.145***	0.0391***	0.0733***	0.0491***
	(10.82)	(6.28)	(11.89)	(3.87)
bedrooms	0.154***	0.178***	0.190***	0.201***
	(4.67)	(12.38)	(13.38)	(7.60)
beds	-0.0559*	-0.0372***	-0.0377***	-0.00906
	(-2.33)	(-3.95)	(-3.83)	(-0.50)
availability_30	0.0164***	0.0147***	0.0144***	0.00611***
	(13.02)	(13.31)	(16.34)	(5.41)
HostListCount	-0.000570	0.00109***	0.000767***	0.00110*
	(-0.93)	(6.29)	(4.18)	(2.15)
BathNum	-0.0771***	0.258***	0.0513***	0.157***
	(-4.31)	(14.89)	(3.94)	(6.37)
Lc	0.0847**	0.0982***	0.102***	0.297***
	(3.01)	(5.16)	(5.91)	(8.57)
distCenter	-0.0437***	-0.0423***	-0.0455***	-0.0546***
	(-9.79)	(-12.58)	(-15.78)	(-9.81)
VrNum	-0.0456***	-0.0256***	-0.0383***	-0.0157**
	(-6.57)	(-4.98)	(-8.20)	(-2.91)
Rating	0.0507*	0.0819***	0.0794***	0.0471*
	(2.51)	(5.06)	(5.72)	(2.33)
minimum_nights	-0.00241***	-0.000354	-0.00144***	0.00209***
	(-6.81)	(-1.40)	(-6.65)	(4.36)
AmNum	0.00132	0.00196*	0.00140	0.00734***
	(0.88)	(2.04)	(1.59)	(4.62)
Am_Wifi	-0.0924	-0.0233	-0.0929*	0.0775
	(-1.29)	(-0.50)	(-2.27)	(0.62)
Am_Heating	-0.105**	-0.0267	-0.0516*	-0.0274
	(-2.72)	(-1.00)	(-2.18)	(-0.56)
Am_Ac	-0.0180	-0.0545*	-0.0193	-0.164***

	(-0.63)	(-2.36)	(-1.00)	(-5.35)
Am_Pool	0.163^{*}	0.152^{***}	0.231^{***}	0.198^{***}
	(2.56)	(4.11)	(6.54)	(3.59)
Am_Kitchen	-0.178^{***}	0.160^{***}	-0.176^{***}	0.0171
	(-6.24)	(3.92)	(-7.76)	(0.30)
Am_FrPark	-0.0756^{**}	-0.0875^{***}	-0.0895^{***}	-0.162^{***}
	(-2.71)	(-4.12)	(-4.93)	(-4.88)
Am_Jacuzzi	0.364^{*}	0.0780	0.246^{**}	0.263
	(2.36)	(0.81)	(2.74)	(1.46)
Am_Washer	0.0507^{*}	0.0221	0.0482^{**}	0.0358
	(2.12)	(1.16)	(3.01)	(1.35)
Am_Workspace	-0.0366	-0.0148	-0.0461^{*}	-0.0501
	(-1.26)	(-0.70)	(-2.44)	(-1.83)
Am_TV	0.156^{***}	0.139^{***}	0.165^{***}	0.201^{***}
	(6.61)	(4.45)	(8.59)	(5.33)
Am_Luggage	0.0567^{*}	-0.000950	0.0360^{*}	-0.0493
	(2.09)	(-0.05)	(2.13)	(-1.61)
Am_PPark	0.159^{***}	0.104^{***}	0.145^{***}	0.0890^{**}
	(4.72)	(4.94)	(7.36)	(2.90)
Am_Grill	0.0398	0.0861^{***}	0.107^{***}	0.0896
	(1.01)	(3.35)	(4.61)	(1.73)
Entire			0.555^{***}	0.660^{***}
			(29.25)	(18.42)
Constant	4.452^{***}	4.080^{***}	4.116^{***}	3.427^{***}
	(33.63)	(39.42)	(48.94)	(19.35)
Observations	6124	8598	13193	1529
R-squared	0.477	0.568	0.678	0.800
Adj. R-squared	0.469	0.564	0.676	0.795
F-stat	60.14	125.6	321.3	172.8

Source: Inside Airbnb

Table 13: Airbnb lising price regressed on listing's characteristics by property type (GLS and Bootstrap)

	(1) Not Entire Listing		(2) Entire Listing		(3) Not Apartment		(4) Apartment	
	b/t	se	b/t	se	b/t	se	b/t	se
Apt	-0.284***	0.0616	0.0546	0.0292				
	(-4.61)		(1.87)					
Nbhd	-0.00665***	0.00159	-0.00305*	0.00125	-0.00562***	0.000897	-0.00614***	0.00141
	(-4.18)		(-2.45)		(-6.27)		(-4.35)	
accommodates	0.145***	0.0355	0.0391***	0.00736	0.0733***	0.00893	0.0491***	0.0135
	(4.10)		(5.31)		(8.21)		(3.65)	
bedrooms	0.154***	0.0434	0.178***	0.0175	0.190***	0.0176	0.201***	0.0284
	(3.56)		(10.15)		(10.81)		(7.07)	
beds	-0.0559	0.0329	-0.0372**	0.0115	-0.0377***	0.00964	-0.00906	0.0196
	(-1.70)		(-3.24)		(-3.91)		(-0.46)	
availability_30	0.0164***	0.00177	0.0147***	0.00145	0.0144***	0.00104	0.00611***	0.00130
	(9.25)		(10.10)		(13.82)		(4.69)	
HostListCount	-0.000570	0.000496	0.00109***	0.000138	0.000767***	0.000138	0.00110*	0.000555
	(-1.15)		(7.87)		(5.57)		(1.99)	
BathNum	-0.0771***	0.0103	0.258***	0.0247	0.0513***	0.0154	0.157***	0.0276
	(-7.47)		(10.43)		(3.33)		(5.68)	
Lc	0.0847**	0.0304	0.0982***	0.0224	0.102***	0.0162	0.297***	0.0367
	(2.79)		(4.38)		(6.30)		(8.08)	
distCenter	-0.0437***	0.00546	-0.0423***	0.00445	-0.0455***	0.00299	-0.0546***	0.00487
	(-8.00)		(-9.50)		(-15.19)		(-11.20)	
VrNum	-0.0456***	0.00655	-0.0256***	0.00540	-0.0383***	0.00486	-0.0157**	0.00534
	(-6.96)		(-4.74)		(-7.89)		(-2.93)	
Rating	0.0507	0.0264	0.0819***	0.0225	0.0794***	0.0168	0.0471	0.0244
	(1.92)		(3.64)		(4.72)		(1.93)	
minimum_nights	-0.00241***	0.000472	-0.000354	0.000543	-0.00144***	0.000340	0.00209***	0.000540
	(-5.10)		(-0.65)		(-4.24)		(3.88)	
AmNum	0.00132	0.00145	0.00196	0.00104	0.00140	0.000898	0.00734***	0.00204
	(0.91)		(1.88)		(1.56)		(3.59)	
Am_Wifi	-0.0924	0.0734	-0.0233	0.0567	-0.0929*	0.0445	0.0775	0.159
	(-1.26)		(-0.41)		(-2.09)		(0.49)	
Am_Heating	-0.105**	0.0335	-0.0267	0.0184	-0.0516*	0.0209	-0.0274	0.0419
	(-3.14)		(-1.45)		(-2.47)		(-0.65)	
Am_Ac	-0.0180	0.0336	-0.0545*	0.0216	-0.0193	0.0211	-0.164***	0.0325
	(-0.54)		(-2.52)		(-0.92)		(-5.05)	

Am_Pool	0.163*	0.0823	0.152***	0.0407	0.231***	0.0331	0.198***	0.0515
	(1.98)		(3.73)		(6.98)		(3.85)	
Am_Kitchen	-0.178***	0.0304	0.160***	0.0374	-0.176***	0.0290	0.0171	0.0490
	(-5.86)		(4.26)		(-6.05)		(0.35)	
Am_FrPark	-0.0756**	0.0261	-0.0875***	0.0241	-0.0895***	0.0195	-0.162***	0.0246
	(-2.89)		(-3.62)		(-4.60)		(-6.58)	
Am_Jacuzzi	0.364**	0.133	0.0780	0.0692	0.246***	0.0737	0.263**	0.0928
	(2.73)		(1.13)		(3.33)		(2.84)	
Am_Washer	0.0507	0.0260	0.0221	0.0227	0.0482**	0.0163	0.0358	0.0315
	(1.95)		(0.97)		(2.97)		(1.14)	
Am_Workspace	-0.0366	0.0283	-0.0148	0.0214	-0.0461*	0.0191	-0.0501	0.0304
	(-1.29)		(-0.69)		(-2.42)		(-1.65)	
Am_TV	0.156***	0.0288	0.139***	0.0413	0.165***	0.0221	0.201***	0.0357
	(5.42)		(3.37)		(7.46)		(5.63)	
Am_Luggage	0.0567*	0.0260	-0.000950	0.0204	0.0360	0.0184	-0.0493	0.0285
	(2.18)		(-0.05)		(1.95)		(-1.73)	
Am_PPark	0.159**	0.0502	0.104***	0.0231	0.145***	0.0244	0.0890*	0.0350
	(3.16)		(4.49)		(5.95)		(2.54)	
Am_Grill	0.0398	0.0361	0.0861**	0.0304	0.107***	0.0217	0.0896	0.0517
	(1.10)		(2.84)		(4.95)		(1.73)	
Entire					0.555***	0.0247	0.660***	0.0322
					(22.49)		(20.53)	
Constant	4.452***	0.161	4.080***	0.126	4.116***	0.0959	3.427***	0.198
	(27.66)		(32.31)		(42.90)		(17.33)	
Observations	6124		8598		13193		1529	
R-squared	0.477		0.568		0.678		0.800	
Adj. R-squared	0.469		0.564		0.676		0.795	
F-stat								

The standard error is generated using bootstrap. Source: Inside Airbnb

Table 14: Airbnb lising price regressed on listing's characteristics by property type (Bootstrap and GLS)

	(1) Not Entire Listing		(2) Entire Listing		(3) Not Apartment		(4) Apartment	
	b/t	se	b/t	se	b/t	se	b/t	se
Apt	-0.284*** (-3.51)	0.0808	0.0546 (1.88)	0.0290				
Nbhd	-0.00665*** (-5.01)	0.00133	-0.00305* (-2.45)	0.00125	-0.00562*** (-5.10)	0.00110	-0.00614*** (-3.97)	0.00155
accommodates	0.145*** (4.12)	0.0353	0.0391*** (4.79)	0.00817	0.0733*** (9.87)	0.00743	0.0491** (3.22)	0.0152
bedrooms	0.154*** (5.27)	0.0293	0.178*** (9.73)	0.0183	0.190*** (12.09)	0.0157	0.201*** (6.79)	0.0296
beds	-0.0559 (-1.46)	0.0382	-0.0372** (-3.18)	0.0117	-0.0377** (-3.25)	0.0116	-0.00906 (-0.46)	0.0197
availability_30	0.0164*** (8.31)	0.00197	0.0147*** (11.80)	0.00125	0.0144*** (13.50)	0.00107	0.00611*** (5.13)	0.00119
HostListCount	-0.000570 (-1.27)	0.000448	0.00109*** (7.66)	0.000142	0.000767*** (5.90)	0.000130	0.00110* (2.11)	0.000522
BathNum	-0.0771*** (-4.21)	0.0183	0.258*** (13.62)	0.0189	0.0513*** (3.45)	0.0149	0.157*** (6.67)	0.0235
Lc	0.0847** (3.22)	0.0263	0.0982*** (4.86)	0.0202	0.102*** (5.09)	0.0200	0.297*** (6.66)	0.0446
distCenter	-0.0437*** (-7.96)	0.00548	-0.0423*** (-10.97)	0.00385	-0.0455*** (-14.24)	0.00319	-0.0546*** (-10.28)	0.00531
VrNum	-0.0456*** (-7.45)	0.00612	-0.0256*** (-5.40)	0.00473	-0.0383*** (-6.58)	0.00582	-0.0157** (-3.15)	0.00497
Rating	0.0507* (2.53)	0.0200	0.0819*** (4.78)	0.0171	0.0794*** (6.44)	0.0123	0.0471 (1.69)	0.0278
minimum_nights	-0.00241*** (-6.49)	0.000371	-0.000354 (-0.75)	0.000471	-0.00144*** (-4.08)	0.000354	0.00209** (3.10)	0.000675
AmNum	0.00132 (0.88)	0.00149	0.00196 (1.62)	0.00121	0.00140 (1.47)	0.000953	0.00734*** (3.84)	0.00191
Am_Wifi	-0.0924 (-1.11)	0.0833	-0.0233 (-0.38)	0.0614	-0.0929 (-1.82)	0.0509	0.0775 (0.47)	0.164
Am_Heating	-0.105** (-3.09)	0.0340	-0.0267 (-1.16)	0.0229	-0.0516 (-1.92)	0.0269	-0.0274 (-0.73)	0.0372
Am_Ac	-0.0180 (-0.48)	0.0372	-0.0545 (-1.88)	0.0290	-0.0193 (-0.99)	0.0195	-0.164*** (-5.74)	0.0286

Am_Pool	0.163*	0.0816	0.152**	0.0487	0.231***	0.0394	0.198**	0.0659
	(1.99)		(3.12)		(5.86)		(3.01)	
Am_Kitchen	-0.178***	0.0351	0.160***	0.0432	-0.176***	0.0284	0.0171	0.0465
	(-5.09)		(3.70)		(-6.19)		(0.37)	
Am_FrPark	-0.0756**	0.0292	-0.0875***	0.0240	-0.0895***	0.0181	-0.162***	0.0377
	(-2.59)		(-3.65)		(-4.94)		(-4.29)	
Am_Jacuzzi	0.364*	0.145	0.0780	0.0845	0.246**	0.0777	0.263***	0.0669
	(2.50)		(0.92)		(3.16)		(3.94)	
Am_Washer	0.0507	0.0284	0.0221	0.0281	0.0482**	0.0176	0.0358	0.0274
	(1.78)		(0.79)		(2.74)		(1.31)	
Am_Workspace	-0.0366	0.0347	-0.0148	0.0223	-0.0461**	0.0176	-0.0501	0.0309
	(-1.05)		(-0.66)		(-2.61)		(-1.62)	
Am_TV	0.156***	0.0366	0.139***	0.0354	0.165***	0.0248	0.201***	0.0371
	(4.26)		(3.93)		(6.64)		(5.42)	
Am_Luggage	0.0567	0.0361	-0.000950	0.0196	0.0360	0.0239	-0.0493	0.0257
	(1.57)		(-0.05)		(1.50)		(-1.92)	
Am_PPark	0.159**	0.0535	0.104***	0.0214	0.145***	0.0245	0.0890*	0.0404
	(2.97)		(4.85)		(5.93)		(2.20)	
Am_Grill	0.0398	0.0359	0.0861**	0.0297	0.107***	0.0288	0.0896	0.0470
	(1.11)		(2.90)		(3.72)		(1.90)	
Entire					0.555***	0.0242	0.660***	0.0325
					(22.91)		(20.28)	
Constant	4.452***	0.135	4.080***	0.116	4.116***	0.0911	3.427***	0.216
	(33.09)		(35.14)		(45.18)		(15.90)	
Observations	6124		8598		13193		1529	
R-squared	0.477		0.568		0.678		0.800	
Adj. R-squared	0.469		0.564		0.676		0.795	

The standard error is generated using bootstrap. Source: Inside Airbnb

Table 15: Airbnb lising price regressed on listing's characteristics by property type (Negative Binomial)

	(1) Not Entire Listing b/t	(2) Entire Listing b/t	(3) Not Apartment b/t	(4) Apartment b/t
price				
Apt	-0.140***	0.0352*		
	(-3.94)	(2.14)		
Date	-0.00257	0.0353***	-0.00668	0.0598***
	(-0.44)	(8.11)	(-1.63)	(7.36)
Nbhd	-0.00334**	-0.00394***	-0.00658***	-0.00536***
	(-3.11)	(-5.78)	(-9.80)	(-3.90)
accommodates	0.187***	0.0437***	0.0821***	0.0544***
	(16.58)	(9.94)	(16.91)	(4.62)
bedrooms	0.235***	0.169***	0.217***	0.189***
	(8.31)	(17.09)	(19.74)	(7.65)
beds	-0.0188	-0.0282***	-0.0309***	-0.00919
	(-1.00)	(-4.36)	(-4.20)	(-0.57)
availability_30	0.00956***	0.00845***	0.00771***	0.00451***
	(13.28)	(14.71)	(15.10)	(4.66)
HostListCount	-0.00342***	0.000521***	-0.0000387	-0.0000147
	(-8.39)	(4.55)	(-0.32)	(-0.03)
BathNum	-0.102***	0.279***	0.0441***	0.160***
	(-7.96)	(23.60)	(4.41)	(6.96)
Lc	0.135***	0.0973***	0.128***	0.289***
	(6.87)	(7.46)	(10.45)	(9.14)
distCenter	-0.0242***	-0.0441***	-0.0383***	-0.0513***
	(-7.76)	(-19.63)	(-18.65)	(-9.97)
VrNum	-0.0564***	-0.0204***	-0.0518***	0.00207
	(-13.10)	(-6.79)	(-18.01)	(0.40)
Rating	-0.0550***	0.0595***	0.0138	0.0313
	(-3.49)	(5.75)	(1.33)	(1.80)
minimum_nights	-0.00197***	0.00158***	-0.000244	0.00235***
	(-8.37)	(8.95)	(-1.67)	(5.38)
AmNum	-0.00218*	0.000169	-0.00157*	0.00387**
	(-2.01)	(0.27)	(-2.48)	(2.73)
Am_Wifi	-0.0867	0.0502	-0.0187	0.0709
	(-1.89)	(1.81)	(-0.70)	(0.62)
Am_Heating	-0.0394	0.0163	0.0187	0.0102

	(-1.43)	(0.94)	(1.12)	(0.23)
Am_Ac	0.146***	-0.00593	0.100***	-0.153***
	(7.63)	(-0.42)	(7.63)	(-5.47)
Am_Pool	-0.0649	0.160***	0.169***	0.164***
	(-1.45)	(6.58)	(6.63)	(3.43)
Am_Kitchen	-0.0344	0.205***	-0.0509**	0.0172
	(-1.68)	(7.47)	(-3.08)	(0.33)
Am_FrPark	-0.180***	-0.145***	-0.185***	-0.132***
	(-8.69)	(-10.17)	(-13.75)	(-4.26)
Am_Jacuzzi	0.304**	0.0116	0.190**	0.240
	(2.75)	(0.18)	(2.92)	(1.47)
Am_Washer	-0.0425*	-0.0836***	-0.101***	0.0203
	(-2.46)	(-6.94)	(-8.87)	(0.89)
Am_Workspace	-0.100***	-0.0314**	-0.105***	-0.0568*
	(-5.66)	(-2.65)	(-9.17)	(-2.38)
Am_TV	0.0862***	0.203***	0.122***	0.221***
	(5.13)	(9.81)	(8.78)	(6.35)
Am_Luggage	0.0280	0.0188	0.0236	0.0124
	(1.45)	(1.50)	(1.94)	(0.44)
Am_PPark	0.603***	0.0847***	0.343***	0.0431
	(24.96)	(6.09)	(24.24)	(1.61)
Am_Grill	0.0656*	0.102***	0.166***	0.0584
	(2.33)	(6.11)	(10.02)	(1.32)
Entire			0.443***	0.647***
			(31.90)	(19.93)
Constant	4.826***	4.026***	4.577***	3.435***
	(46.88)	(55.96)	(70.45)	(21.17)
/				
lnalpha	-1.117***	-1.563***	-1.177***	-2.065***
	(-63.45)	(-103.97)	(-98.40)	(-55.27)
Observations	6124	8598	13193	1529
Pseudo R-squared	0.0584	0.0557	0.0663	0.120

Source: Inside Airbnb

Table 16: Airbnb lising price regressed on listing's characteristics by distance to center

	(1) Less than median distance b/t	(2) Larger than median distance b/t
Apt	0.0682***	0.0294
	(4.23)	(1.19)
Date	0.0339***	0.0391***
	(7.31)	(7.91)
Nbhd	-0.00551***	-0.00636***
	(-7.09)	(-8.17)
accommodates	0.112***	0.119***
	(15.63)	(19.81)
bedrooms	0.229***	0.228***
	(14.95)	(17.34)
beds	-0.0315*	-0.0333***
	(-2.53)	(-4.34)
availability_30	0.00953***	0.00805***
	(13.42)	(13.31)
HostListCount	0.00137***	0.000892***
	(12.00)	(6.03)
BathNum	0.0150	-0.0516***
	(1.37)	(-4.30)
Lc	0.196***	0.0579***
	(10.92)	(4.24)
distCenter	-0.104***	-0.0187***
	(-15.56)	(-7.34)
VrNum	-0.0215***	-0.0216***
	(-6.27)	(-6.81)
Rating	0.0837***	0.0782***
	(7.70)	(6.35)
minimum_nights	0.00101***	-0.00256***
	(3.74)	(-14.37)
AmNum	0.00232**	0.00237***
	(3.03)	(3.51)
Am_Wifi	-0.0353	-0.0900**
	(-1.14)	(-3.08)
Am_Heating	-0.0130	-0.0286

	(-0.73)	(-1.71)
Am_Ac	-0.0728***	-0.0310*
	(-4.11)	(-2.46)
Am_Pool	0.203***	0.349***
	(8.96)	(9.40)
Am_Kitchen	0.0205	-0.0671***
	(0.95)	(-4.18)
Am_FrPark	-0.113***	-0.0105
	(-6.78)	(-0.71)
Am_Jacuzzi	0.188***	0.314***
	(3.35)	(4.77)
Am_Washer	-0.0497**	0.0828***
	(-2.96)	(7.17)
Am_Workspace	0.0354*	-0.0316*
	(2.50)	(-2.42)
Am_TV	0.306***	0.236***
	(14.41)	(16.99)
Am_Luggage	-0.0237	0.0222
	(-1.45)	(1.68)
Am_PPark	0.103***	0.173***
	(6.49)	(7.70)
Am_Grill	0.152***	0.00952
	(6.74)	(0.53)
Constant	3.882***	3.708***
	(51.70)	(43.78)
Observations	6309	8413
R-squared	0.512	0.611
Adj. R-squared	0.510	0.609
F-stat	267.2	520.4

Source: Inside Airbnb

Table 17: Airbnb lising price regressed on listing's characteristics by multiple cities

	(1) Austin b/t	(2) Chicago b/t	(3) Denver b/t	(4) Los Angeles b/t	(5) Nashville b/t	(6) New York City b/t
Entire	0.496***	0.565***	0.401***	0.616***	0.240***	0.532***
	(61.20)	(56.80)	(34.84)	(146.78)	(19.21)	(151.36)
Apt	0.0287	0.231***	0.251***	0.0871***	0.0739**	0.138***
	(1.29)	(6.77)	(4.84)	(8.45)	(2.80)	(10.25)
Date	0.00588*	-0.0229***	-0.00498	-0.00338*	0.0385***	0.00492***
	(2.14)	(-7.89)	(-1.56)	(-2.36)	(14.50)	(3.86)
Nbhd	-0.00553***	0.000256***	-0.0000306*	0.0000336***	-0.00126***	0.000159***
	(-32.04)	(13.88)	(-2.11)	(4.32)	(-4.40)	(26.50)
accommodates	0.0488***	0.0634***	0.0475***	0.0638***	0.0749***	0.0935***
	(17.94)	(23.41)	(13.52)	(37.07)	(30.68)	(60.49)
bedrooms	0.127***	0.0783***	0.158***	0.234***	0.0987***	0.108***
	(19.08)	(11.42)	(22.18)	(44.56)	(17.28)	(37.63)
beds	-0.00250	0.0232***	-0.0344***	-0.0494***	-0.00531**	-0.0132***
	(-0.84)	(5.03)	(-5.74)	(-22.53)	(-3.04)	(-5.50)
availability_30	0.00333***	0.0121***	0.00713***	0.00915***	0.0100***	0.0131***
	(9.57)	(29.34)	(16.30)	(57.87)	(26.52)	(68.67)
HostListCount	0.00209***	0.000265***	0.000575***	-0.000375***	-0.00140***	-0.000317***
	(11.53)	(8.23)	(4.27)	(-13.89)	(-17.68)	(-5.94)
BathNum	0.226***	0.143***	0.209***	0.0920***	0.0812***	0.0986***
	(34.27)	(16.75)	(30.40)	(19.44)	(13.63)	(21.96)
Lc	0	-0.0801***	0.193***	0.246***	0	-0.410***
	(.)	(-5.46)	(18.38)	(69.16)	(.)	(-3.36)
distCenter	-0.00604***	-0.0262***	-0.0249***	0.00219***	-0.0276***	-0.0443***
	(-30.06)	(-31.73)	(-31.82)	(21.02)	(-36.03)	(-131.28)
VrNum	-0.0151***	-0.0434***	-0.0196***	0.000455	-0.00222	-0.0220***
	(-10.61)	(-23.04)	(-11.51)	(0.56)	(-1.74)	(-30.49)
Rating	0.0504***	0.0503***	0.101***	0.0369***	0.108***	0.0276***
	(7.95)	(6.59)	(6.86)	(11.50)	(9.07)	(14.05)
minimum_nights	-0.00107***	-0.00118***	-0.000802	-0.00164***	-0.00101*	-0.00171***
	(-4.28)	(-8.97)	(-1.56)	(-15.56)	(-2.01)	(-15.03)
AmNum	0.00288***	0.00569***	0.00530***	0.00324***	0.00121***	0.00740***
	(9.44)	(15.16)	(14.58)	(20.98)	(3.62)	(42.56)
Am_Wifi	-0.0201	-0.0452***	-0.0766***	-0.0459***	-0.0158	-0.0453***
	(-1.91)	(-3.66)	(-6.57)	(-6.11)	(-1.02)	(-6.36)

Am_Heating	0.0643***	-0.0406***	0.0136	0.0438***	0.0101	-0.0115**
	(9.68)	(-4.46)	(1.65)	(11.80)	(1.36)	(-3.07)
Am_Ac	0.0857***	-0.00791	0.105***	-0.0190***	0.0199*	0.0578***
	(10.12)	(-0.92)	(13.50)	(-5.50)	(2.18)	(16.91)
Am_Pool	0.107***	0.0967***	0.0843***	0.158***	0.145***	0.122***
	(16.59)	(7.95)	(7.27)	(38.70)	(16.71)	(13.89)
Am_Kitchen	-0.102***	-0.266***	-0.0781***	-0.109***	-0.105***	-0.222***
	(-10.38)	(-19.75)	(-6.47)	(-21.44)	(-10.29)	(-40.09)
Am_FrPark	-0.146***	-0.221***	-0.0939***	-0.0665***	-0.193***	-0.123***
	(-11.53)	(-24.39)	(-5.84)	(-12.92)	(-14.66)	(-35.59)
Am_Jacuzzi	0.101**	0.0447	0.174***	0.0509***	-0.121*	0.114***
	(3.17)	(1.35)	(5.26)	(5.34)	(-2.14)	(4.23)
Am_Washer	-0.0580***	0.0441***	-0.0111	0.0418***	-0.0188*	0.0722***
	(-7.91)	(5.58)	(-1.47)	(12.11)	(-2.53)	(23.91)
Am_Workspace	-0.0390***	-0.0579***	-0.0345***	-0.0500***	-0.0468***	0.00916**
	(-6.11)	(-7.97)	(-4.66)	(-15.05)	(-7.79)	(3.07)
Am_TV	0.0846***	0.142***	0.142***	0.145***	0.0948***	0.112***
	(8.14)	(12.04)	(9.06)	(29.13)	(4.95)	(34.89)
Am_Luggage	-0.0315***	0.00613	-0.0347***	-0.0285***	0.0243***	-0.0224***
	(-4.93)	(0.80)	(-4.55)	(-7.42)	(3.47)	(-6.05)
Am_PPark	-0.00197	0.0304***	0.0463**	0.0885***	0.100***	0.0493***
	(-0.14)	(3.68)	(2.81)	(14.41)	(7.00)	(11.57)
Am_Grill	0.0614***	0.00131	0.0574***	0.0616***	0.0331***	0.0709***
	(9.13)	(0.16)	(7.80)	(15.58)	(4.60)	(12.42)
Constant	3.911***	3.968***	3.247***	3.453***	4.122***	4.139***
	(103.13)	(82.85)	(40.49)	(179.40)	(42.40)	(278.83)
Observations	45785	22035	16288	114861	24183	115463
R-squared	0.543	0.624	0.612	0.650	0.647	0.596
Adj. R-squared	0.543	0.624	0.612	0.650	0.647	0.595
F-stat	1788.9	1254.8	665.9	5866.0	1364.5	5374.0

Source: Inside Airbnb

Semaglutide Drugs: Navigating Public Policy Challenges in the Treatment of Diabetes and Obesity

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Introduction:

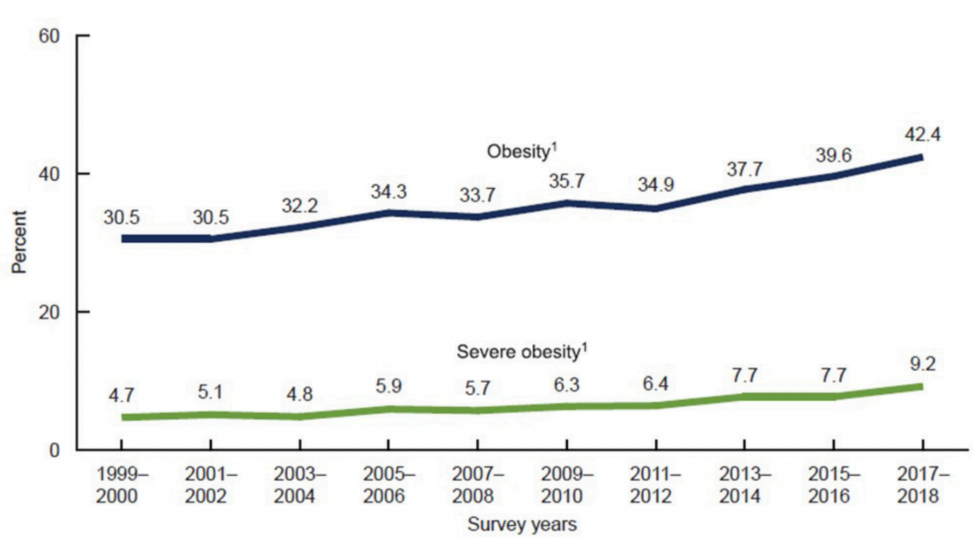
Obesity has long been acknowledged as an epidemic in the United States, and poses severe health concerns, as a leading risk factor for diabetes. The obesity epidemic also presents a substantial financial burden on American citizens due to its correlation with costly diseases such as diabetes and heart disease. In 2019, adult obesity was linked to an average of around $2,000 in excess annual medical costs per person, contributing to a staggering near $173 billion in annual expenditures. The impact extends to children as well, with obesity associated with just over $100 in excess costs per person and a total of $1.3 billion in medical spending (Ward et al., 2021). These alarming figures are indicative of a growing financial strain; projections suggest that the economic toll will only escalate as nearly 60% of today's children are anticipated to be obese by the age of 35 (ibid). As policymakers attempt to confront this mounting crisis, the question arises: what is the true value of weight loss for both individuals and society at large?

The emergence of semaglutide drugs has commenced a new era of medical possibilities for alleviating obesity. Semaglutide drugs have gained notoriety, since their release in 2021, for their efficacy in reducing weight and improving glycemic control. This essay will explore these new drugs, specifically how they are priced and regulated, as a case study for the US pharmaceutical industry. I will summarize the birth of this new line of drugs, the way they are priced, and the surge of demand for them both for treating diabetes and obesity, and cosmetic weight loss, due to their off-label usage by celebrities and thereby presence in the media. I will also examine how the United States government, health care providers, the Food & Drug Administration (FDA), and other regulatory bodies have created layers of challenges for manufacturers of these drugs to enter and navigate the anti-obesity medication (AOM) market, and for these drugs to ultimately reach and treat the citizens who need them most. How these drugs continue to be regulated and priced in the future will determine how accessible they are to patients, how insurers cover them, and ultimately overall health spending.

Scientific Background:

Diabetes, a chronic metabolic disorder characterized by elevated blood sugar levels, affects over 34 million Americans, with an estimated 1.5 million new cases diagnosed each year (CDC 2021). Furthermore, obesity, a leading risk factor for diabetes, affects more than 40% of the U.S. population (CDC 2020).

Figure 1: Trend in age-adjusted obesity and severe obesity prevalence among adults ages 20 and over: United States, 1999 - 2018



Source: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2018.

As seen in Figure 1, obesity among adults in the United States has only become more prevalent over time; its upward sloping trend line suggests it will continue to grow in the future. Obesity is a highly prevalent, chronic disease requiring long-term management; clinical complications of obesity affect almost every organ system, and the impact of obesity on morbidity, mortality, and health care costs is substantial (Bergmann et al. 2022). Obesity, and being overweight in general, are serious conditions that can be associated with some of the leading causes of death such as heart disease, strokes, and diabetes (FDA). The CDC recommends "lifestyle modification" as the foundation of treatment for individuals suffering from obesity, however, such changes typically achieve only modest weight loss that is often regained and can be extremely time-intensive. Drug developers worldwide invest heavily in designing pharmacological treatments for obesity that can help patients achieve greater and long-lasting weight loss.

In June of 2021, the FDA approved a new medication for diabetes, obesity, and long-term weight management: subcutaneous semaglutide (Ghusn et al. 2022). Semaglutide drugs[1] are glucagon-like peptide-1s (GLP-1) receptor agonists and mimic the GLP-1 hormone that is released in the gastrointestinal tract in response to eating. The GLP-1 hormone's role is to prompt the body to produce more insulin, which reduces blood glucose; in high amounts, GLP-1 can interact with the parts of the brain that reduce appetite by signaling a feeling of fullness (FDA 2023). Semaglutide medications have been studied extensively by scientists since their FDA approval and have proven to be effective at managing weight loss in patients. In large, randomized controlled trials, patients receiving semaglutide – Ozempic or Wegovy – at the maximum dosage of 2.4 mg, lost a mean of 6% of their weight after three months and 12% of their weight by six months (Ghusn et al. 2022).

The medications warn patients of side effects, most commonly including nausea, headache, and fatigue[2] (FDA 2021). The medications have also been found to have a potential risk of thyroid C-cell tumors. Zepbound was even found to have caused thyroid C-cell tumors in rats, according to a study done by the FDA prior to their approval of the medication (FDA 2023). Thus, manufacturers warn that

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[1] Semaglutide injections activate receptors of hormones secreted from the intestine (glucagon-like peptide-1 (GLP-1) and glucose-dependent insulinotropic polypeptide (GIP) to reduce appetite and food intake. This decreases after-meal blood glucose and delays gastric emptying (FDA 2023).
[2] The most common side effects of Wegovy include nausea, diarrhea, vomiting, constipation, abdominal pain, headache, fatigue, dyspepsia, dizziness, abdominal distension, eructation, hypoglycemia (low blood sugar) in patients with type 2 diabetes, flatulence, gastroenteritis, and gastroesophageal reflux disease (FDA).

semaglutide should not be used in patients with a personal or family history of medullary thyroid carcinoma or in patients with a rare condition called Multiple Endocrine Neoplasia syndrome type 2. In general, public perception of the drugs is positive, with little proven evidence of negative side effects.

Development and Demand:

Novo Nordisk, a Danish pharmaceutical company, leads the pack of developers of the new semaglutide treatments; they sell the two most popular drugs being taken for weight loss: Wegovy and Ozempic. Ozempic is approved to reduce the risk of heart attack, stroke, or death in adults with type 2 diabetes mellitus and known heart disease, whereas the Wegovy injection is approved to help patients with obesity or excess weight, who also have weight-related medical problems, to lose weight and keep the weight off (Hopkins and Armour 2023). Novo Nordisk has been incredibly profitable in the development and sale of these medications; their market capitalization reached $413 billion in the second quarter of 2023, surpassing the total GDP of their home country by $7 billion (Waddick 2023). Ozempic and Wegovy are two of the currently four FDA-approved semaglutide products. The others are Rybelsus tablets and the Zepbound injection, which was approved just a month ago on November 8, 2023 (FDA 2023). All four medications are only available with a prescription, and there are no approved generic versions yet.

Since their launch in 2021, these drugs have gained extraordinary attention in the media, as celebrities like Elon Musk have taken to social media to applaud their effectiveness with significant weight loss. Social media posts, like Musk's, have sparked the interest of people who are unaffected by obesity or diabetes, but looking to lose weight for cosmetic reasons. According to a survey taken in July of 2023 by the Kaiser Family Foundation, nearly half of US adults (45%) said they would be interested in taking a weight-loss drug they knew to be safe and effective (Montero et al. 2023). Nearly six in 10 (59%) of those who are interested are currently trying to lose weight, and half (51%) of those who are trying to lose weight, aim to lose fewer than 10 pounds (ibid.). While it is legal for doctors to prescribe semaglutide injections to US citizens for unofficial use, cost and insurance coverage contribute to whether consumers would purchase the products; only 16% would remain interested in purchasing and using the drugs if they were not covered by insurance (ibid.). The drugs are not typically covered by insurance and many employers are cutting coverage for semaglutide medications in their insurance offerings because of the drugs' high price tag – typically over $1,300 per month.

The Pricing Problem:

United States retail prescription drug spending increased by 91 percent, adjusted for inflation, from 2000 to 2020, and spending is expected to further increase by 5 percent by year through 2030. This trend is driven, in part, by increasing list prices for drugs (CMS 2022). In 2022, overall US drug prices – including brands and generics – were nearly three times as high as prices in comparison countries, even after adjusting for estimated US rebates. The gap between US prices and prices in other countries was larger for brand-name originator drugs; US prices for these drugs exceeded non-US prices by 400 percent (ASPE, 2024). Accordingly, semaglutide injections are significantly more expensive in the US than in comparable developed nations. As seen in Figure 2, in the US, a one-month supply of Ozempic (1mg) costs $936, Rybelsus (7mg) costs $936, Wegovy (2.4mg) costs $1,349, and Mounjaro (15mg) – the Eli Lilly version of the drug – costs $1,023 (Amin et al. 2023). On average, taking any of these medications for a year would cost a patient $13,000, which does not include the cost, though minimal, of the medical tools needed to administer the injections.

Figure 2: Prices for popular semaglutide drugs by country

	▼ Ozempic (semaglutide, injection)	Rybelsus (semalglutide, tablets)	Wegovy (semaglutide, injection)	Mounjaro (tirzepatide, injection)
U.S.	**$936**	**$936**	**$1,349**	**$1,023**
Japan	$169	$69	-	$319
Canada	$147	$158	-	-
Switzerland	$144	$147	-	-
Germany	$103	-	$328	-
Netherlands	$103	$203	$296	$444
Sweden	$96	$103	-	-
United Kingdom	$93	-	-	-
Australia	$87	-	-	-
France	$83	-	-	-

Note: List prices in $USD based on web searches as of August 15, 2023. Prices are for one-month supply of Ozempic 1mg, Rybelus 7mg, Wegovy 2.4mg, and Mounjaro 15mg. Some drugs are not available in all countries and prices were unable to be found in other countries. Some drugs are approved for diabetes and prescribed off-label for weight loss.

Source: Amin et al. 2023.

Just across the border in Canada, the same dosages of Ozempic and Rybelsus cost about $150. Prices appear even lower in Australia, Japan, and European countries. For example, in France, a monthly dosage of Ozempic is $83, and in Japan, a monthly dosage of Rybelsus is a mere $69 a month (ibid.). Even Wegovy, notorious for its higher prices, is over $1,000 cheaper in the Netherlands than in the US[3]. Figure 2 also highlights the differences in drug presence between the United States and the other nations studied. While all four drugs are approved and available for sale in the US, many other countries' governments have only approved one or two of the medications. This could be the result of lower demand or need for the medications in other countries, as the obesity rate in the US is nearly two times higher than the OECD average (Gunja et al. 2023). Thus, nations with lower obesity rates have fewer citizens who require medical treatments for the disease.

[3] Looking four months in advance, it is cheaper to fly to the Netherlands from Boston, stay for two nights, purchase a month's supply of Wegovy, and fly back to Boston, than it is to purchase a month's supply of the medication in the United States (Boston). A roundtrip, nonstop flight on Delta airlines from BOS to AMS from March, 1st 2024 to March 3rd, 2024 is $540. A two-night stay at the Four Elements Hotel Amsterdam for the same dates would total around $170. Finally, including the purchase of the prescription at $296 would result in a trip total of $1,006, resulting in over $300 of savings compared to purchasing the medication in the United States (Delta.com and Google.com).

The shockingly high US prices for semaglutide drugs consequently puts a spotlight on the disparity between those who can and cannot afford to pay the high out-of-pocket price for these new AOMs, thus creating a situation in which those who need the drug for Type 2 diabetes – the approved indication – cannot access it due to its cost (Waddick 2023). Observation of higher US drug prices imply that Americans are paying disproportionately for pharmaceutical R&D that benefits the world at large. (Beall et al. 2021). This occurs because American pharmaceutical companies are paying the massive R&D costs, recently estimated to be over $2 billion per drug (Reanne et al. 2022), for the development of most groundbreaking drugs.

The prices displayed in Figure 2 are "list prices" – the prices listed to consumers by insurers – which are generally very different from the "net prices" of the drugs, which reflect confidential rebates negotiated between health insurers and pharmacy benefit managers, as well as market conditions and negotiating leverage (Kolata 2023). Most manufacturers do not reveal their drugs' net prices, however, according to economists Ippolito and Levy (2023), there are data sources that can be used to estimate them. A study by these economists for the American Enterprise Institute, characterizes prices for the four notable GLP-1s this paper has discussed: Ozempic, Wegovy, Rybelsus, and Mounjaro. In the study, the authors assembled data on the full list price – at the monthly level – of each product from manufacturer websites and collected information about coupons offered by manufacturers. They also used SSR Health US' Brand Rx net Price Tool which provides an estimate of the net price for a month's supply of each product, which they define as the average payment the manufacturer receives from the insurance company for the drug after all price concessions, including rebates and coupons (ibid.). The net price reflects payments across commercial purchasers, government purchasers, and those paying cash.

Figure 3: List versus Net Prices for popular semaglutide drugs

	Ozempic	Rybelsus	Wegovy	Mounjaro
List Price	$936	$936	$1,349	$1,023
Implied Net Price (Received by Manufacturer)	$290	$337	$701	$215*
Value of Manufacturer Coupons for Patient Out-of-Pocket Cost				
Insured with Coverage for Product	$150	$300	$225	$150
Insured Without Coverage for Product	—	—	$500	$575
Cash Pay (No Coverage)	—	—	$500	—
Implied Out-of-Pocket Cost with Coupons				
Insured Without Coverage	$936	$936	$849	$448
Uninsured	$936	$936	$849	$1,023

Note: Discounts are calculated as four-quarter moving averages, when possible. See Table 1 for estimates. * Mounjaro does not yet have four quarters of data, so its net price is based only the most recent quarter. Because it is based on less data, we view Mounjaro's net price estimate with greater uncertainty.
Source: List pricing data and coupon availability are taken from manufacturer websites, all accessed in August 2023. Net prices are based on data from SSR Health. Data on coupons are from NovoCare (n.d.a. and n.d.b.) and Mounjaro (n.d.).

Source: American Enterprise Institute, *Estimating the Cost of New Treatments for Diabetes and Obesity*, Economic Perspectives (Ippolito and Levy 2023).

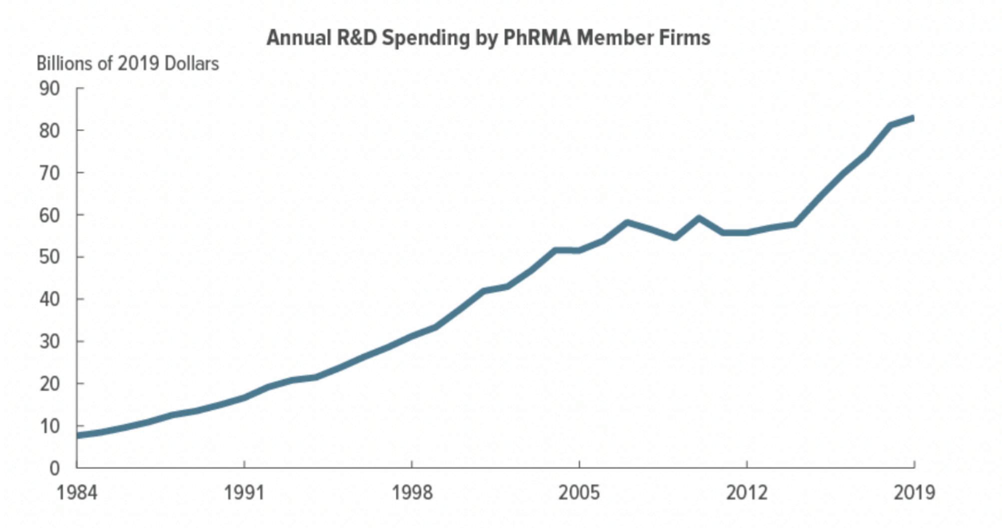
As seen in Figure 3, the drugs' estimated list prices are consistently higher than their net price, with Ozempic's list price being over 300% of its implied net price and Mounjaro's list price being about 375% of its net price. These findings indicate that list prices are an incomplete summary of the pricing landscape for semaglutide drugs. While some consumers can purchase the drugs directly from manufacturers at, or near, the undiscounted net prices, list prices are often most relevant because of how they are treated by insurers (ibid.). Insurers typically determine cost sharing as a percentage of the drug's list price, rather than the lower net price they paid to the manufacturer for the drug. This increases costs for customers taking the medications while implicitly reducing premiums for nonusers. Many policymakers have criticized this arrangement because it generates unpredictable cost-sharing amounts for patients and partly undermines health insurance's purpose of improving quality of life, instead motivating a focus on saving money.

The U.S. Pharmaceutical Industry:

The United States' healthcare system does not provide universal coverage to citizens, who instead utilize different means to obtain health insurance. About half of the US population receives health insurance from their employer or a family member's employer, 20% of the population is enrolled in Medicaid, 14% in Medicare, 7% purchase insurance directly from the marketplace, 2% are covered under benefits from the military or Veterans Affairs, and about 9% are uninsured (Inteso and Isaacs 2021). The federal government is involved in the healthcare system through Medicare, a federal health insurance program mostly for people 65 years and older. Medicare is the country's largest buyer of prescription drugs; according to government data, Medicare spent over $145 billion on prescription drugs in 2021 (Amin et al. 2023). This $145 billion expenditure did not include semaglutide drugs, as current federal law prohibits Medicare from covering weight-loss drugs (ibid.). The US healthcare system also lacks a centralized pricing or reimbursement authority; instead, drug prices are set by manufacturers and are negotiated by private insurance providers and Pharmacy Benefit Managers.

It remains undisputed that the United States' pharmaceutical industry is the global leader in drug innovation. In 2014, the global top forty drugs sold were broken down by manufacturer and home country, to find that the number of drugs produced by Switzerland, the UK, Sweden, France, and Japan, combined – the next largest markets for pharmaceuticals – is still below that of the United States: nineteen versus twenty-one (Schweitzer and Lu 2018). The great demand for pharmaceuticals in the United States, and among other developed nations, is derived from the demand for health, and the market for pharmaceuticals is unique in many ways. The industry's most differentiating characteristic is that it is heavily dependent on fixed costs, rather than the marginal cost of producing an additional unit of medication – which is extremely low. The fixed costs span years research and development (R&D) before products even make it to market (ibid.).

Figure 4: Annual Spending on Research & Development by large pharmaceuticals



Source: Congressional Budget Office, Research and Development in the Pharmaceutical Industry (2021)

The Pharmaceutical Research and Manufacturers of America (PhRMA) represents the nation's leading biopharmaceutical research companies and advocates for public policies that encourage the discovery of important, new medicines for patients by biopharmaceutical research companies. Member firms include Novo Nordisk, Pfizer, Merck, Johnson & Johnson, and Eli Lilly, among other large drug developers and manufacturers. As presented in Figure 4, these firms are now spending upwards of $80 billion dollars in R&D for new drugs, emphasizing the incredibly large number of resources poured into the creation of new medications in the United States.

Before medications even reach the US market, they must be approved by the Food & Drug Administration (FDA) to ensure their safety and efficacy. Even before approval by the FDA, drug manufacturers can obtain patents – government-granted rights that typically last 20 years from the date of filing – that legally prevent potential competitors from selling versions of the product that has been patented. These patents can be filed not only for the combination of active ingredients in the medication, but also on aspects of drug formulations, methods of use, and delivery devices; in the case of semaglutide injections, the injection pen used to administer the medication (FDA 2023). Manufacturers employ strategies such as obtaining large numbers of different patents on the same product, obtaining new patents on products even after FDA approval, and settling patent litigation brought by potential generic competitors to maintain and elongate their periods of exclusivity (ibid.). Semaglutide nets drug manufacturers more than $10 billion per year in the US alone, and every additional year of brand-name market exclusivity may be associated with hundreds of millions of dollars in manufacturer revenue, offering an incredible financial incentive to block competition (ibid.).

(Alhiary 2023) analyzed ten different 10 semaglutide drugs on their patent strategies and found that on average, drug manufacturers listed with the FDA a median of about 20 different patents per product, including a median of 17 patents filed before FDA approval and 2 filed after FDA approval. The manufacturers are so incentivized by market exclusivity, that they are willing to expend effort in filing additional patent applications long before their drugs are approved. Another interesting finding was that more than half of all patents listed on semaglutide drugs were on the delivery devices – injection pens – rather than active ingredients (ibid.). Not only did these manufacturers obtain large numbers of patents, but the median total duration of the patent's expected protection, after FDA approval, was 18 years. Firms that produce generic versions of drugs have tried to challenge patents on semaglutide drugs but have been entirely unsuccessful. Generic manufacturers for 4 of the 10 products in the study, submitted challenges seeking FDA approval for their drug prior to the expiration of the brand-name patent's exclusivity (ibid.). However, none of the challenges resulted in an approved generic, with many of the lawsuits being terminated or decided in favor of the brand-name manufacturer (ibid.).

Many economists argue that patent protection is an incredible incentive for pharmaceutical firms to continue to innovate, and that it is essential for firms to be able to maintain their investments in R&D. While this is true, drug manufacturers like Novo Nordisk have strategically used patents to create government-sanctioned monopolies and oligopolies for themselves. The monopolization of these manufacturers allows them to set extremely high prices, and in the absence of competition, or effective price controls by the government or regulatory bodies, pharmaceutical companies can even engage in price gouging and undercut the negotiating power of payers (Ginsburg and Lieberman 2020). These monopolized markets restrict access to patients with no, or less comprehensive, drug insurance coverage; they deprive patients of quick access to lower-priced, essentially identical substitutes – generics (Beall et al. 2021). In the monopolized semaglutide drug market, the drugs are not allocated efficiently, as they would be under perfect competition. The monopolist – manufacturers like Novo Nordisk or Eli Lilly – supply the drugs at a quantity at which their marginal cost and marginal revenue intersect, instead of where marginal cost meets demand. The lower quantity of drugs produced allows the monopolist to price the drugs higher, further up the demand curve, creating a greater producer surplus, lower consumer surplus, and a certain amount of deadweight loss not obtained by either producer or consumer.

The problem of low supply within a monopolized market is relevant with the new semaglutide drugs, as many developed countries have observed and reported on the shortages of the drugs. The Australian Government's Department of Health and Aged Care, under the Therapeutic Goods Administration (TGA), has established an alert page regarding the shortage of Ozempic (semaglutide) – and similar drugs Trulicity (dulaglutide) and Mounjaro (tirzepatide) – due to the increased global demand that has impacted availability. They note that Novo Nordisk has recently advised the TGA and the Ozempic Medicine Shortage Action Group that supply throughout the rest of the year and into 2024 will be limited. To combat this limited supply, the TGA has been forced to ask health professionals not to prescribe Ozempic to new patients, instead to conserve supply for patients who are already stabilized on the medication and cannot find suitable alternatives.

International Perspective:

Most of the United States' peer, developed, nations do cover all their citizens through universal healthcare, and have centralized pricing authorities. Whether centrally determined, or privately negotiated, an important aspect of pharmaceutical pricing today is drug evaluation, in which purchasers – insurance plans, PBMs, and even government programs – determine whether drug therapies are really “worth” the cost. These centralized pricing and approval authorities are a means by which peer nations determine safety, efficacy, and affordability of the drugs they allow to be sold to their citizens.

In the European Union, countries vary in their approaches to pharmaceutical regulation and pricing, as each member state has its own healthcare system. However, there is a centralized agency, the European Medicines Agency, that assesses and approves medications for the entire EU. Some countries, like France and Germany, institute cost-effectiveness evaluations to aid in the determination of drug pricing, ensuring that expensive medications are balanced with their health benefits. While that kind of analysis is performed in the US, it is by private entities and researchers, and the results do not dictate prices. The UK also has one of these regulatory bodies, the National Institute for Health and Care Excellence, which evaluates the cost-effectiveness of medications, including anti-obesity drugs, and recommends whether they should be funded by the National Health Service.

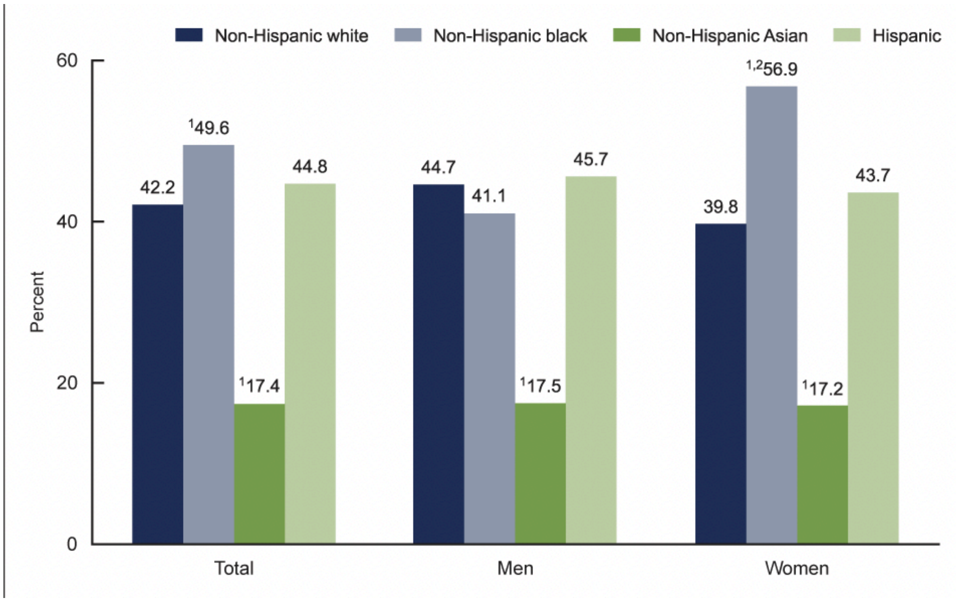
Outside of Europe, Canada has a universal healthcare system through which the government regulates prescription drugs, which can even be subject to negotiation by provincial governments. The country’s health department, Health Canada, approves medications for safety and efficacy before they can be sold in the Canadian market, much like the FDA in the United States. Then, through public drug plans, the Canadian government negotiates prices with pharmaceutical companies, both domestic and foreign, to ensure that medications, including AOMs like semaglutide are accessible and affordable for patients (Martin et al. 2018). Both Australia and Japan are known for maintaining drug evaluation programs and strict pricing systems to ensure affordability and efficacy of the drugs they allow.

The developed nations described above cover all their citizens through universal healthcare and price medications centrally to prioritize access and affordability in their healthcare systems. However, these prioritizations do come with downsides including wait times, budget constraints, and lesser innovation. Universal healthcare can create challenges in terms of access to certain medical treatments or long wait times for elective procedures in some countries. Centralized pricing and negotiation authorities may lead to budget constraints, limiting the availability of certain expensive or innovative, new treatments. This can sometimes result in delayed access to cutting-edge medications and therapies. Finally, universal coverage healthcare systems might stifle innovation by reducing the potential return on investment for pharmaceutical companies. This could impact the amount of research and development being done on new medical possibilities, and the frequency with which new medications are created and approved.

Ethical Considerations:

In evaluating if, and how, the federal government should respond to high prices – prices that are inaccessible to much of the United States' population – and supply shortages for essential medications like semaglutide drugs, ethical considerations are an important factor. Drug pricing in the United States has exacerbated income inequality, as high drug prices disproportionately affect lower-income and non-insured individuals and families struggling to afford necessary treatments; high priced treatments become a larger share of lower-income individuals, and families, spending. This might persuade lower-income individuals to avoid treatments even if they would be beneficial in the long term, or reduce doses. High healthcare costs create inequality in access which ultimately adds to disparities in health outcomes and well-being. As mentioned above, over 40% of adults in the US suffer from obesity; however, large disparities exist across racial, ethnic, and income groups. Nearly half of non-Hispanic Black and over 40% of Hispanic adults have obesity versus only one-third of non-Hispanic White adults (Wright et al. 2023).

Figure 5: Obesity prevalence among adults by sex and race



Source: NCHS, National Health and Nutrition Examination Survey, 2017–2018 (Hales et al. 2020)

The National Health and Nutrition Examination Survey by the National Center for Health Statistics presents obesity prevalence among US adults by sex and race, utilizing data from 2017-2018. Though the statistics have evolved slightly since then, Figure 5 depicts similar percentages of obesity across ethnic groups as the current statistics cited above. The figure showcases that non-Hispanic black women had a higher prevalence of obesity than non-Hispanic black men, as well as any other racial group. However, there were no significant differences in prevalence between men and women among non-Hispanic white, non-Hispanic Asian, or Hispanic adults (Hales et al. 2023) These percentages illustrate the disproportionate burden of obesity, and the treatment of it, on underserved populations.

Novo Nordisk provides savings cards and plans including a “My$99Insulin” program to make insulin, via a different medication they manufacture, more affordable for those in need. This raises the question: why does the same manufacturer charge over $1000 a month for their new semaglutide drug that prompts the body to produce insulin – essentially the same thing? (Inteso and Isaacs 2021). Furthermore, negative externalities on the general population are generated by the pricing strategy of the

US pharmaceutical industry, and the sky-high prices of these medications. Obesity and its associated health problems, such as diabetes, have external costs that are not fully borne by individuals, including: increased healthcare spending, reduced workforce productivity, and a higher burden on the healthcare system. This externality is not reflected in the pricing of the medications, which leads to an inefficient allocation of the resource.

Another ethical consideration regarding the shortage in supply and inaccessible high prices of these semaglutide medications, is the distribution of fake medications which can be harmful to consumers. In May of 2023, the TGA detected fake semaglutide being illegally imported into Australia. Counterfeit products may contain undeclared and hazardous ingredients that could cause serious risk to the health and safety of consumers. The Australian government warned citizens that any product not manufactured by Novo Nordisk claiming to contain semaglutide is likely to be fake or counterfeit, as there are currently no generic versions of semaglutide being lawfully manufactured (TGA 2023). In 2023, Police in England performed raids and made arrests in a crackdown on illegal sales of semaglutide medication. In the U.K., it is illegal to advertise prescription-only drugs to the public (Forbes 2023). Andy Morling, deputy director of criminal enforcement at the country's Medicines and Healthcare Regulatory Agency, who previously arrested a man suspected of selling the drug illegally online, warned U.K. citizens that "the very best that could happen to you is you lose your money in a scam... and the worst that could happen is you end up hospitalized" (ibid.).

Finally, the promotion of these medications might be perpetuating the negative effects of social media on adolescents who deal with eating disorders and questions about body image. The advertisements on social media platforms could lead children and teens to believe that there is a magic pill out there for weight loss.

Policy Suggestions:

There are many ways in which the US federal government and regulatory bodies can intervene to make semaglutide, and anti-obesity medication in general, more accessible for Americans. There are currently two main types of protection that guarantee a competition-free period for new prescription drugs, such that most new drugs are doubly protected from competition in the first few years after market entry: patent protection, granted by the country's patent office, and market protection, enforced through a drug regulator. Neither mechanism considers the anticipated public health impact at the given price of the new drug product (Beall et al. 2021). This could be changed by introducing competition earlier in these markets or reducing the reign of the pharmaceutical monopolies via extended periods of market exclusivity. The US government could revise their process for granting patents, perhaps by reforming the patent systems to prevent the abuse of patent protections that may result in extended monopolies. introduce market competition via Congress granting the FDA more flexibility in approving generic drug-device combinations. The FDA currently requires generic firms to develop drug-device combinations that patients can use in just the same way as brand-name versions based on an identical label. However, the FDA has called upon Congress to allow, in 2024, labeling changes on generic drug-device combinations, which would enable generic manufacturers to develop drug-device combinations that differ from brand-name versions – in a slight, clinically interchangeable way – thereby avoiding infringing their patents. —and more easily avoid infringing their patents (Alhiary 2023). The government could shorten patent durations in general or create rules for specific-case patent exemptions in situations where, like semaglutide, a drug addresses vast unmet medical needs.

The US government could set price controls, via price negotiation mechanisms, or ceilings – minimum allowable prices – for the cost of medications, particularly for essential or life-saving drugs like semaglutide. Some economists suggest the implementation of a value-based pricing model, based on cost-benefit analysis, where the price of medications is determined based on their demonstrated clinical value and cost-effectiveness. This methodology would involve measuring the quality-adjusted life years, or a similar value measure, to anticipate the therapeutic and public health gains of a drug and calculate the period of exclusivity such that new drugs with the greatest public health impact would receive the longest exclusivity periods within a certain minimum and maximum range of years (ibid.). Linking drugs' proposed prices to the duration of their regulatory-based exclusivities would still incentivize drug developers to invest in R&D and innovation, while motivating them to introduce their products at lower prices. Additionally, if regulating pricing, the US government could also implement a tiered pricing system that allows for different pricing levels based on income or affordability, as well as demonstrated need. This way, lower-income individuals, specifically those with diagnosed diabetes, severe obesity, and obesity, can access medications at a reduced cost, while those with higher incomes, and those who want to consume the drug for minor weight loss, pay a higher price, ensuring financial sustainability.

The government could also opt for an even more simple reform to the pharmaceutical industry, and force pharmaceutical companies to be transparent regarding various pharmaceutical activities, but specifically the pricing of their drugs. To do so, the federal government, or a regulatory body like the FDA, could require pharmaceutical companies to disclose detailed information about their pricing strategies – for example, explain increases in drug prices that exceed threshold amounts they establish for the drug upon approval – and profits. A manufacturer could also be obliged to report how much it had spent on manufacturing the drug, and its overall investments in R&D so that consumers might have a greater understanding of why high prices are needed to pay back such massive investments. In general, greater transparency can shed light on pricing practices and promote accountability.

Another policy the US government could institute is regulation of advertising and marketing by insurers and pharmaceuticals, as the attention on these drugs, caused by massive marketing expenditures, is generating demand from consumers that cannot be met. A report by MediaRadar on weight-loss-related and diabetes drug advertising spend on television, print, top newspapers, and online channels including websites, streaming channels, podcasts, social platforms, during the first half of 2023, found that nearly $500 million had been invested in advertising diabetes and weight loss prescriptions, marking a 21%

year-on-year increase from $405 million at the same midpoint of 2022 (Adams 2023). Perhaps unsurprisingly, the top four prescriptions in these categories were Eli Lilly's diabetes drug Jardiance and Novo Nordisk's semaglutide drugs: Ozempic, Rybelsus, and Wegovy (ibid.). Together, these companies accounted for $358 million in advertisement sales, which is nearly three quarters (73%) of the total spend in their prescription categories. The study also found that advertising spend increased by about 20% for Ozempic, 40% for Rybelsus and more than 1,000% for Wegovy in 2023 over 2022 (ibid.). In June of 2023, NBC reported more than 4,000 ads for Ozempic-style drugs were found running on Instagram and Facebook on a given day (Ingram 2023). In May, Novo Nordisk declared it was pausing its ads, citing a shortage of semaglutide and a desire not to stimulate further demand. Most of the ads on social media have not come from the drugmaker, and instead are run by online pharmacies and lesser-known marketers who use social media ads to drive fast sales growth at nearly any cost (ibid.). Online pharmacies, medical spas, and diet clinics are capitalizing on a surge of interest in weight-loss drugs. Meta, the company that owns the social media platforms, has a policy that requires advertisers to obtain written permission and provide evidence of an appropriate license before they can promote prescription drugs, and only online pharmacies, telehealth providers and drugmakers are eligible. However, this policy is clearly not being enforced effectively, which is something the US government could increase pressure for the platforms to do.

Currently, federal law in the United States does not restrict drug companies from advertising any kind of prescription drugs, even ones that can cause severe injury, addiction, or withdrawal effects. The FDA also does not have any authority to affect the amount of money drug companies spend on ads, and does not require ads to inform citizens of cost, whether or not there is a generic version of the drug, and if changes in one's behavior could help their condition – such as diet and exercise which are effective for the remediation of obesity – which is the case for many consumers of semaglutide medications who seek cosmetic weight loss (FDA 2023). In contrast, the Australian Government's TGA currently prohibits the advertisement of prescription Ozempic, and semaglutide in general, warning that advertising the medication to the public can result in jail time and penalties above $11 million for corporations and greater than $1 million for individuals, which increasingly relevant in an age of social media and influencer marketing (TGA 2023). This policy was established in the wake of abundant marketing of Ozempic that contributed to a global shortage of the medicine, and has even contributed to shortages of alternatives, such as Trulicity (dulaglutide), as type 2 diabetes patients move to new treatments (TGA 2023). The rationale behind their policy restricting advertising is that therapeutic goods are not ordinary consumer goods; generally, consumers of health products are a more vulnerable consumer group than the general population of a country, and it is important to have advertising laws in place to protect the public from inappropriate and misleading claims. The policy also serves to ensure that advertisements are balanced, accurate, and support Australians to make informed health care choices. Instead of restricting advertisement of semaglutide drugs entirely, the United States government could impose advertising or marketing ceilings for pharmaceutical companies, or change the standards for advertisements, requiring them to be approved in advance.

Policies in Action:

Currently, the United States government has passed two acts that aim to negotiate drug pricing with pharmaceutical companies, including manufacturers of semaglutide drugs, in coming years. In 2019, the House of Representatives passed "H.R. 3,", the Elijah E. Cummings Lower Drug Costs Now Act, which will require the Secretary of Health and Human Services to negotiate with drug manufacturers over the domestic prices of certain high-priced, single-source drugs. The Act asserts that negotiated maximum price may not exceed 120% of the average price in Australia, Canada, France, Germany, Japan, and the United Kingdom, or, if such information is unavailable, 85% of the U.S. average manufacturer price (Congress 2020). Hopefully, the negotiated prices would better reflect the clinical importance of a treatment and the existence or absence of alternative treatments (Ginsburg and Lieberman 2020). This Act, if instituted in the next year, could have major effects on the price of semaglutide in the U.S. where prices are up to ten times greater than in peer nations, as noted above in Figure 2 (Amin 2023). The Act also includes a policy for drug manufacturers who do agree to participate in negotiations or that failed to agree to a negotiated price, which legislators foresaw as a potential challenge, requiring them to subject to an excise tax on sales of the drug. Between income taxes they already pay, and this new excise tax, manufacturers are at risk to lose money (not recoup their R&D investments) if the drug are sold in the United States. The excise tax on sales would have a similar effect as if the drug had not been approved for sale in the U.S., or as if the drug were excluded from a formulary – a national list of drugs that insurers were allowed to cover. Therefore, the potential use of the excise tax could place pressure on drug manufacturers in negotiations and thereby could lower drug prices and federal spending (Adams 2019).

However, a price will be paid in innovation for the lower drug cost to consumers. The Congressional Budget Office estimates that under the bill, approximately eight fewer drugs would be introduced to the U.S. market over the years 2020 to 2029, and about 30 fewer drugs over the subsequent decade, whereas under current law, the Food and Drug Administration approves, on average, about 30 new drugs annually or 200 over a decade (CBO 2023). This would be the result of pharmaceuticals having longer payback periods for R&D investments, making investments in R&D less attractive to the manufacturers.

Finally, a common suggestion for the government to reform inaccessible drug prices is to grant Medicare the power to negotiate drug prices. This option is incredibly relevant and timely, as Medicare recently gained the authority to negotiate the prices of certain high-price medications under the Inflation Reduction Act. Two of the ten drugs up for price negotiations next year include Januvia, a diabetes drug from Merck & Co. that had sales of $1.2 billion last year, and Jardiance, a diabetes drug from Eli Lilly (Walker 2023). In its negotiations, Medicare is supposed to consider whether drugs represent a therapeutic advance or fulfill an unmet medical need, R&D costs, and any prior federal funding. An upper bound will also be placed on the negotiated price, however, the Act will shield new drugs from negotiated prices for the first 9 to 13 years on the market in an effort to maintain incentives for R&D and innovation (Hwang et al. 2022). In contrast, most other peer countries typically negotiate drug prices at the time of market entry, and no peer country limits the number of drugs negotiated (Hwang et al. 2022). Generic competition within a given class of medication may enhance the government's leverage in negotiation for all drugs in the class. This is because the Center for Medicare Services (CMS) plans to negotiate based on the net prices of therapeutic alternatives. Thus, if one low-price generic version of a semaglutide were to become available in the US, this may help achieve lower prices for all semaglutide that CMS selects for negotiation (Alhiary 2023).

The announcement of the Inflation Reduction Act has greatly angered pharmaceutical companies, some of whom believe it violates their constitutional rights. Merck, manufacturer of Januvia, has complained about the negotiation program's enforcement rules, including the power to levy an excise tax of up to 95% of a drug's U.S. sales if a pharmaceutical company refuses to sell the drug to Medicare patients (ibid.). Merck asserted that the tax would be coercive and violate the corporations Fifth Amendment right, which bans private property being taken for public use without just compensation (ibid.). The company also said the law would force companies to agree that the government-mandated prices are "fair," violating its free speech rights under the First Amendment. Therefore, the choice of the US government to allow price negotiation on drug prices has not and will not come without significant push back from pharmaceutical companies, which the government will have to factor into consideration as these firms bring in billions of dollars in revenue annually.

Conclusion:

Manufacturers of the newly released semaglutide medications to treat obesity and diabetes have utilized patents granted by the United States Food and Drug Administration, to create periods of market exclusivity, during which they charge extremely high prices for their drugs in the United States. Many citizens who need drugs like semaglutide for the treatment of type 2 diabetes and obesity, are unable to afford them and receive the treatment that is necessary for their survival or could increase their quality-adjusted life years.

The US government has thus far, not intervened in the pricing strategy for these medications; however, they are becoming involved through Medicare price negotiations. There are many ways in which the government could implement policies to help bring down the cost to consumers for necessary medications such as semaglutide. As discussed above, they could introduce competition; price ceilings, tiered pricing, or pricing tied to quality measures; require transparency from manufacturers regarding pricing; and set limits on advertising and marketing spending and technique. Between these potential policies, policymakers and economists hold differing views regarding the role of higher prices in spurring innovation – along with the importance of robust innovation – which results in opposing pressures for limiting price reductions versus seeking to maximize price cuts. In addition, it is often difficult to disentangle views regarding higher prices for innovation from stakeholder politics, as the United States government is a significant regulator of private insurance and directly paying for 35 percent of all health care costs through Medicare, Medicaid, and other programs (Ginsburg and Lieberman 2020).

Overall, setting hard price limits for drugs could lead manufacturers to reduce R&D and innovation, which is extremely important for the amelioration of many health concerns. Instead, lawmakers and regulators should work to develop policies that facilitate timely entry of generic drug-device combinations for semaglutide drugs. For example, reducing the periods of market exclusivity granted by patents, so that manufacturers can earn reasonable returns for limited periods of time, and are therefore incentivized to innovate, but when competition enters the market, the costs of the medication to patients will naturally decrease.

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Inequality in Early Childhood Education across Income Groups and its Implications

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ECON3317

Economics of Inequality

Professor Geoffrey Sanzenbacher

1. Introduction

The early years of a person's childhood intricately shape the trajectory of their future life. During early childhood the foundations of cognitive, social, and behavioral competencies necessary for successfully participating in society are created (Feinstein & Duckworth, 2006). The exposure in these early years influences future health, educational, social, and professional achievements in later life (Gray-Lobe et al., 2023).

However, it has been shown that the socio-economic status (SES) of individuals strongly influences the experiences children make in the first five years of their lives, resulting in a self-perpetuating cycle of unequal opportunity among children of different socio-economic background (Gray-Lobe et al.). While it is hard to influence the experiences children of young age have at home, an important institution able to shape individuals' experiences before attending school is early childhood education and care (ECEC) programs. These programs can positively influence children's health, educational achievements, criminal records and future employment trajectories (Gray Group International, 2023).

Despite the utter importance of these early childhood programs in reducing inequality of opportunity, access to ECEC programs in the United States varies strongly among families from different socio-economic backgrounds. Since the availability of public ECEC programs is still limited, a lot of high-quality institutions offering ECEC are private and fee-based, reducing accessibility for low-income groups (Curry, 2001). To examine the scope of this inequality, this brief will address the question whether the enrollment rates in ECEC programs vary among different income groups.

This brief will be structured as follows: Section 2 will provide important contextual and background information on the effects and availability of ECEC-programs, focusing on the United States. Section 3 will discuss the methods used to conduct the statistical analysis on the question whether participation in ECEC programs varies among income groups and will provide the results of this analysis. The results will be discussed and interpreted in section 5 and conclude with a summary and proposed policy interventions.

2. Background

2.1 The Impact of Early Childhood on Adult Outcomes

The far-reaching importance of early childhood experiences is well-founded throughout the literature. A central reason for unequal outcomes in adulthood is that children from families with a poor socio-economic standing are exposed to more risk factors in the early years of their lives. These risk factors create stressors and challenges that play a pivotal role in perpetuating disparities in economic outcomes. For example, U.S. African-American children, who tend to come from lower-income and less educated families, show strongly reduced kindergarten readiness compared to their white counterparts. These early disparities lay the foundation for self-perpetuating inequality in adult outcomes (Magnuson, 2005).

The exposure to risk factors affects children in numerous different ways. The natural sciences have complied robust evidence that early childhood experiences do not only influence behavioral responses but change the brain structure of toddlers. These structural changes in the brain due to stressful and negative experiences during early childhood lead to higher rates in a range of mental health issues as well as a reduced ability to cope with stressful situations (McEwen, 2003). However, early childhood not only influences behavioral responses and future health, but also a range of economic outcomes, which are moderated by these biological changes. Determining a causal relationship between early childhood experiences and adult outcomes is seldom possible due to selection issues and other confounding effects. However, by exploiting the quasi-random allocation of Yemenite immigrants in more and less developed regions of Israel during the "Operation Magic Carpet" in 1949, Gould et al. (2010) could isolate the effect of the environment children grew up in on economic outcomes in adulthood. Children growing up in a more stable and modern environment obtained higher education, were more likely to be working at age 55, tended to be more integrated into Israeli society and had children that were more likely to experience these positive effects as well.

2.2 Effectiveness of Early Childhood Education and Care Programs

Among the available early childhood interventions, the most effective policies are early childhood education and care (ECEC) programs. General reviews have found that the participation in ECEC programs promotes children's cognitive, social, and emotional development, creating a solid foundation for future academic success. However, the benefits exceed the individual level. ECEC participants have also been shown to have a higher probability of being employed in adulthood as well as show a cleaner criminal record, benefiting society at large (Gray International Group, 2023).

There has been extensive research on the success of specific ECEC interventions that have been implemented in the United States, which yielded, in general, positive but mixed results. Heckman et al. (2010) found that the Perry Preschool Program, implemented between 1962 and 1969 in Michigan, had positive effects on employment outcomes for males, educational outcomes for females, and reduced crime rates for both genders. Evaluations of the presently more relevant Head Start initiative show similar findings, however, the effects tend to be smaller compared to those of the Perry Program, which is likely attributable to quality differences between interventions (Carneiro & Ganja, 2004; Deming, 2009).

These mixed results suggest that there are several factors that moderate the effectiveness of ECEC programs. First, it is essential to acknowledge that the results of ECEC programs on later outcomes are mediated by other factors, such as the literacy environment and socio-economic status of the child's family. Furthermore, the mere attendance of an ECEC program is in many cases not sufficient to enhance future academic, professional and health outcomes (Balladares & Kankaras, 2020), as the quality of the program significantly influences its positive impacts. Additionally, it has been shown that the age of entry in ECEC programs is decisive on its future effects. Evaluating the effects of ECEC programs in OECD member states it could be found that a starting age of three years maximized academic achievement at age 15 for ECEC participants (Balladares & Kankaras, 2020). These findings highlight the importance of not only providing broad accessibility to early childhood interventions but also the necessity to promote high-quality program designs.

2.3 Accessibility of Early Childhood Education and Care Programs in the United States

Compared to other western countries, the United States has a strongly elevated rate of child poverty, with 11 million children under the age of 18 living in poverty, making up 16% of their age group. Therefore, ensuring the accessibility to publicly funded ECEC programs is of central importance to mitigate the self-perpetuating effects of educational and income disparities in early childhood.

Generally, access to ECEC programs in the U.S. has improved strongly, yielding an average 46% increase in enrollment rates for children of ages three to five over the last century. Over this period, the five-year-olds have particularly benefited, as enrollment rates in this age group more than tripled (Cascio, 2021). This considerable growth can be seen as a sign of a societal shift towards recognizing the importance of early childhood education.

However, various barriers to the participation in ECEC-programs still exist for disadvantaged U.S. families, particularly prevalent for Hispanic and African American minorities. Possible barriers are, for example, stress experienced due to ethnic or racial discrimination, elevated rates of child illness, or social isolation of the family. Furthermore, the demands of family life can be higher for these families, as work and school schedules must be balanced while dealing with stressors such as housing instability or care responsibilities. Financial and housing-related barriers arise as disadvantaged families tend to live in low-income neighborhoods that have weak transport access and reliability, as well as have low net incomes that creates difficulties in paying the fees related to ECEC programs or managing the costs of transportation to these programs (Beatson, 2022).

As of today, these hurdles remain significant, as private ECEC programs, often fee-based, are the predominant choice for most families that can, if eligible, be supported through childcare subsidies and additional financial assistance through tax provisions (Curry, 2001). However, publicly funded preschools, with the dominant program in the U.S. being the Head Start initiative play a vital role in serving children from families below the federal poverty threshold or subject to other disadvantages.

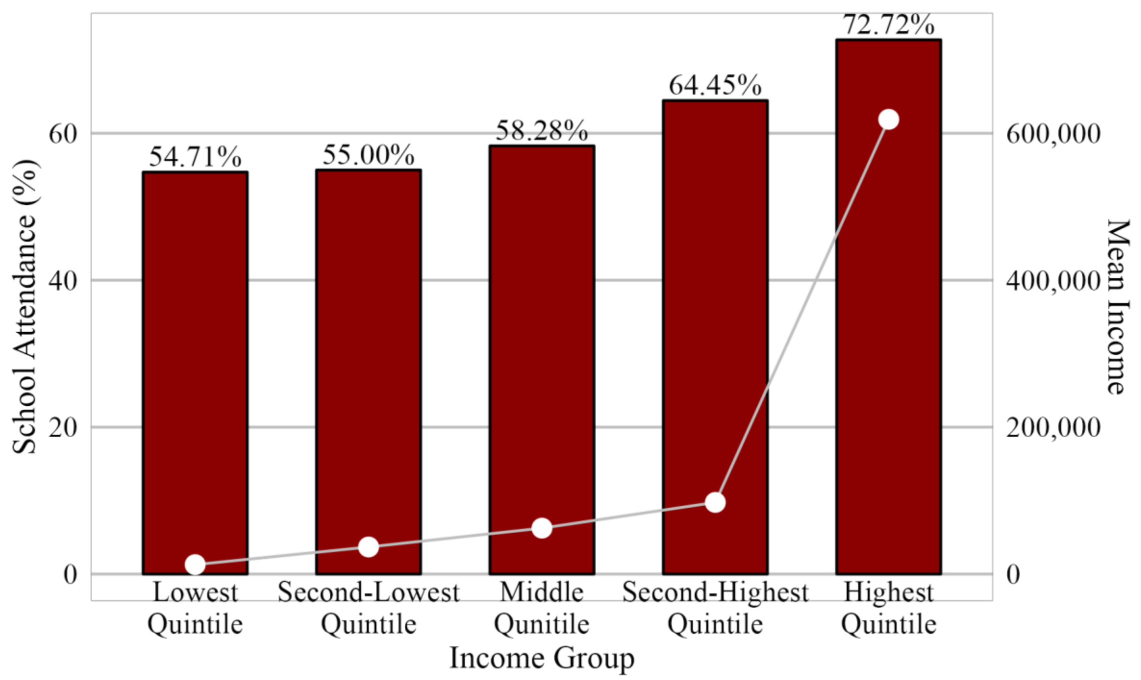
2.4 Introducing the Comprehensive Childhood Initiative Head Start

The Head Start initiative, established in 1965 as part of President Lyndon B. Johnson's war on poverty is the largest publicly funded early education program in the US and serves around 65% of all eligible three to four-year-old children in the country (ECLKC, 2023). Today, there are 2,809 programs in the country with more than 1 million participants (Marshal, 2014). It aims to address the physical, cognitive, and emotional challenges faced by poor children, with the goal of reducing inequality of opportunity and breaking the cycle of disadvantage for children from families with low socio-economic standing. It consists of an educational program that focuses on social-emotional learning, science, math, reading, and language development to improve school readiness, as well as a program that serves nutrition and healthcare to the participating children and their families (ECLKC, 2023). The positive long-term impacts of Head Start is supported throughout the literature, however there is inconsistent evidence on which areas are positively affected (e.g. educational attainment, crime reduction, mortality) as well as on how long these positive effects are visible (GTC, 2002; Ludwig and Miller, 2007). Nevertheless, it is well-established that the returns the program generate exceed its costs.

2.5 Inequality in Access to and Quality of ECEC-Programs

Despite initiatives such as Head Start, the quality and accessibility of ECEC-programs varies for families of different SES. An important indicator of the SES of families is their income, which can be easily assessed and used to determine the scope of inequality in access and quality of ECEC programs. While the quality of ECEC-programs is essential in determining their success, to generate these positive effects, the inequality in the share of enrolled children from different socio-economic backgrounds must be decreased. To detect important points of intervention the following section will examine the ECEC enrollment rates of different income groups, hypothesizing that lower income groups show lower shares of enrollment.

Figure 1. School Enrollment of 3 to 5-year-olds and Mean Income by Income Group



Source: Ruggles et al., IPUMS USA (2022).

3. Empirical Analysis

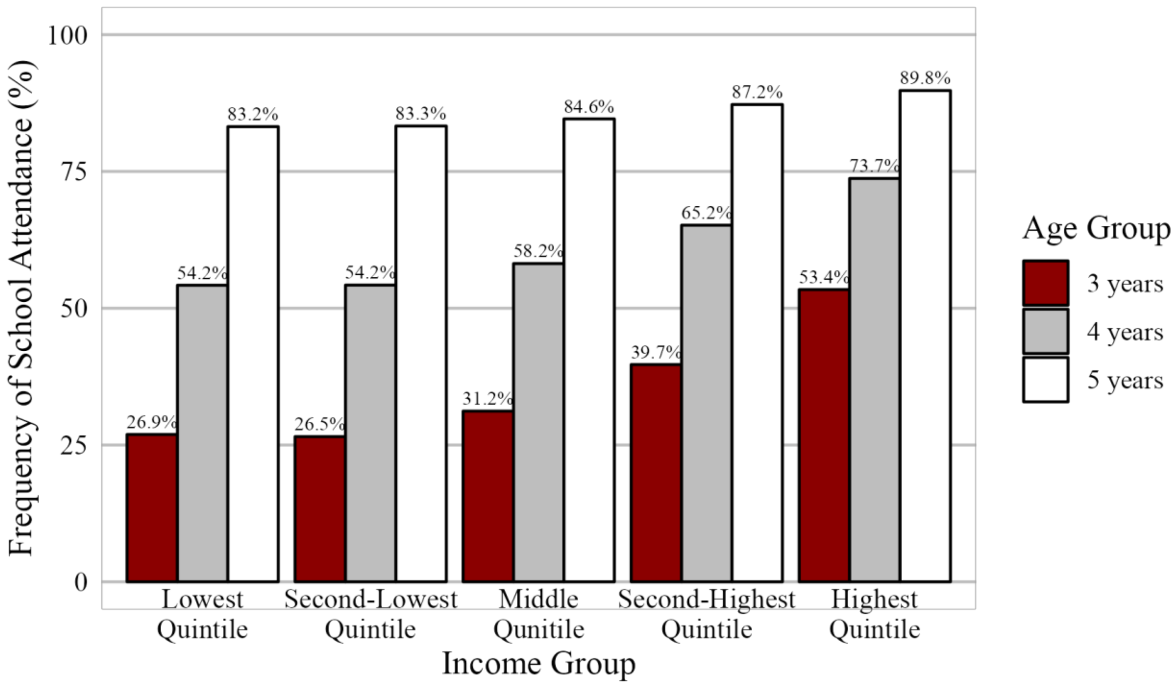
3.1 Methodology

For the analysis, micro-level data on all participants of age three to five that participated in the American Community Survey (ACS, 2022) between 2000 and 2022 was retrieved from the IPUMS USA database.

The variables included in the data analysis are the year in which the surveyed individual participated in the ACS (YEAR), the age of the participant at the time of the survey (AGE), the total family income (FTOTINC), and the school attendance of the surveyed individual (SCHOOL). Total family income reports the total pre-tax income earned by the family of the surveyed individual in the year prior to the survey and is given according to pre-specified intervals. School attendance is reported in a binary variable stating if the individual is or is not attending school at the time questioned. Furthermore, a variable stating the income quintile individuals belong to, as well as the share of individuals of a specific income group and age attending school were calculated.

The empirical analysis was conducted in two steps. First, a multinomial chi-square test was used to determine whether there were differences in school attendance between different income groups. Additionally, three more chi-square tests were conducted to examine the inequality in school enrollment rates between the different age groups.

Figure 2. Relative Frequency of School Enrollment by Income Group and Age



Source: Ruggles et al., IPUMS USA (2022).

3.2 Results

3.2.1 Descriptive Statistics

To summarize the data, the mean income of the income groups and the relative frequencies of school enrollment per income group were calculated. Overall, school enrollment rates were higher for higher income quintiles. However, the lowest two quintiles have almost equal enrollment rates (Figure 1). The gap in enrollment was greater for children of younger ages (Figure 2).

3.2.2 Disparities in School Enrollment Rates by Income Group

To test whether the observed difference in general school enrollment rates for children of ages three to five from different income groups is significant, an omnibus chi-square test was conducted. Income groups one and two had a sample size of N = 413413, while income groups three, four and five had a sample size of N = 413412. School enrollment rates in different income groups showed significant disparities, X^2 (4) = 15734.19, $p < .001$. The real and expected frequencies of school enrollment per income group are illustrated in Table A2 in Appendix A.

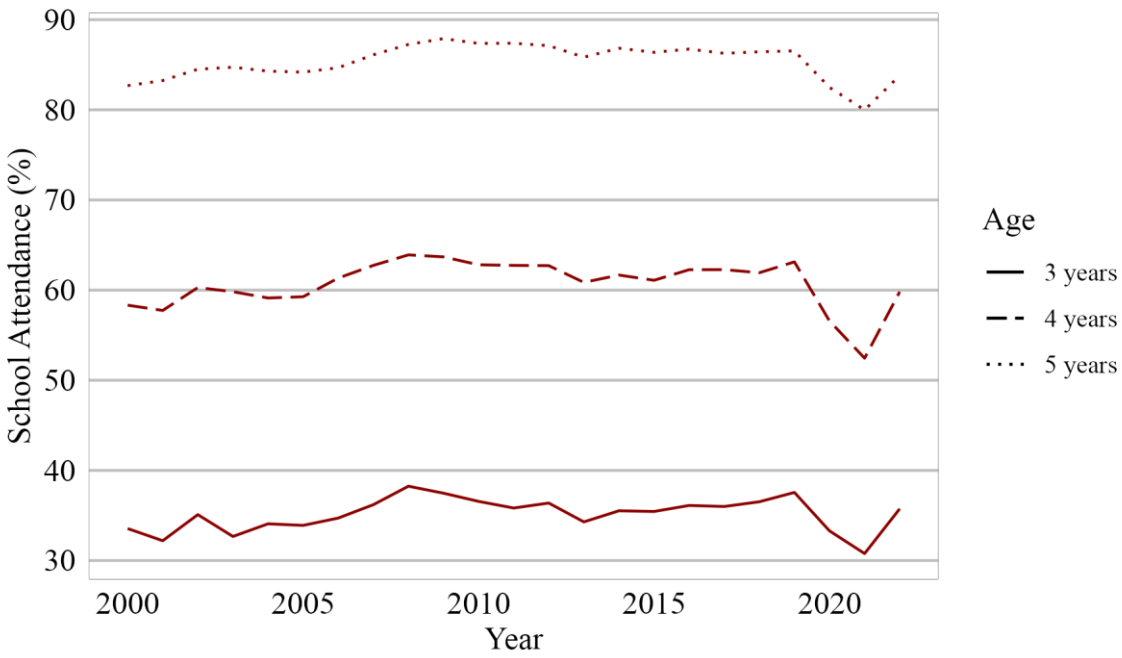
Figure 3. School Enrollment Rates by Income Group between 2000 and 2022

Source: Ruggles et al., IPUMS USA (2022).

3.2.3 Disparities in School Enrollment Rates by Income Group and Age

To determine whether the magnitude of the disparities in school enrollment rates in early childhood found in Section 4.2 vary by age, the sample was split into three separate groups, grouped by age. For all three groups, significant disparities in school enrollment rates between different income groups could be found, however the value of the test statistic decreased with increasing age of the children, implying lower levels of inequality for five-year-olds (three-year-olds: X^2 (4) = 17776.19, p < .001; four-year-olds: X^2 (4) = 6359.96, p < .001, five-year-olds: X^2 (4) = 991.73, p < .001).

Figure 4. School Enrollment Rates by Age between 2000 and 2022



Source: Ruggles et al., IPUMS USA (2022).

4. Conclusion

Summarizing the results, it could be found that across all age groups, significant differences in enrollment exist between income groups, with the upper quintile having the greatest and the two lowest quintiles having the smallest school enrollment rates (Figure 1). These differences in enrollment are exaggerated for children of younger ages, implying that inequality in ECEC-programs is higher for three- and four-year-olds. This is crucial, as the effectiveness of early childhood interventions is greatest when implemented at an early age, as the positive impact of participation in ECEC-programs is significantly decreased for children who enter at ages four or five, compared to children who enter at age three (Balladares & Kankaras, 2020).

Nevertheless, it must be noted that the disparities in enrollment rates of the five income groups between the years 2007 and 2019 have remained stable or have been decreasing for the two lowest income groups (Figure 3). However, this is attributable to decreasing enrollment rates in the upper quintiles, instead of increasing enrollment in the lower income groups.

Additionally, it could be found enrollment rates in ECEC-programs for five-year-olds are significantly higher than for both four- and three-year-old children, and enrollment rates in all age groups have been growing only very slowly since the start of the 21st century, stagnating around 2007. Since 2000, 85.6% of five-year-olds, 61.1% of four-year-olds and 35.5% of three-year-olds have been enrolled in school on average (Figure 4). These insights have several consequences. First, the low general enrollment rates of three-year olds imply that the ECEC-programs have generous opportunity to increase the societal and individual return they generate, since earlier participation offers the greatest benefits. Second, the stagnating increase in enrollment rates can indicate that either the general access to early education programs has not been improving for the past 15 years or that the interest in the participation in said programs has remained stagnant. Combined with the results that inequalities in school enrollment are greatest for the group of three-year-olds, this leads to the conclusion that inequality in opportunity is reinforced in families in the two lowest income quintiles, as enrollment rates among three-year olds are not only low in absolute but also relative levels.

Consequently, the most urgent need to improve access to ECEC-programs still seems to apply to the group of three-year-olds in the lowest two income quintiles. Programs such as Head Start already target this population, however, this study shows that the accessibility of said initiatives must be extended further, to counter stagnating enrollment rates.

Possibilities to achieve this goal are extended funding for said initiative, which has successfully been implemented by the Biden administration in 2022. This increased the funding for programs under the Head Start Act by USD 960 million. However, it is not only necessary to increase the availability of public ECEC programs, but also crucial to actively recruit families that are less likely to participate in these programs to achieve the highest returns. Lastly, efforts to improve and maintain the quality of the programs should be taken to ensure that when broadening accessibility to more families, the returns of the programs remain high.

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6. Appendix A

Table A1. Relative Frequency of School Enrollment by Income Group and Age

Income Quintile	Mean Income	Enrolled in School (%)		
		3 years	4 years	5 years
1) Lowest	12839.34	26.9 %	54.2 %	83.2 %
2) Low	12839.34	26.5	54.2	83.3
3) Middle	62517.21	31.2	58.2	84.2
4) High	97543.67	39.7	65.2	87.2
5) Highest	618946.13	53.4	73.7	89.8

Source: Ruggles et al., IPUMS USA (2022).

Table A2. Real and Expected Frequencies of School Enrollment by Income Group

Income Quintile	Total Observations	Expected Enrollment	Real Enrollment	Confidence Interval (95%)	
				Lower	Upper
1) Lowest	413413	252310	226170	225326	227015
2) Low	413413	252310	227358	226512	228205
3) Middle	413412	252310	240938	240073	241804
4) High	413412	252310	266457	265559	267356
5) Highest	413412	252310	300627	299689	301566

Source: Ruggles et al., IPUMS USA (2022).

Does the Phillips Curve Breakdown?

By Max Manalang and Jacob Chappelear

Introduction

The Phillips Curve and the Phillips relationship describe the positive relationship between inflation and employment. In recent decades, the Phillips Curve has been scrutinized because of inexplicable "breaks" in the curve during the 70's, 80's, and 90's. Stephen Marglin introduces a long-run Keynesian theory in chapter 18 of his *Raising Keynes* that attempts to explain these breaks by illustrating the long-run tradeoff between employment, output, and growth on one hand and inflation on the other. The resulting theory, that aggregate demand *and* aggregate supply matter in the long run for determining employment, growth, and inflation, creates a model of the macro-economy which successfully accounts for the supposed breakdown of the Phillips curve. In chapter 19, Marglin tests his theory against American economic data from 1956 to 2011. In this paper, we attempt to answer the question "Does Stephen Marglin's Long-run Macroeconomic Theory still explain the supposed break-down of the Phillips Curve with 12 additional years of data?" by updating his regression results with the years 2012-2023. We are interested in this question because we believe that there is a possibility that Marglin's theory could no longer stand up to new data and new shocks in unemployment, inflation, and the labor markets due to the COVID-19 pandemic. Ultimately, we find that the regression coefficients are in general agreement with Marglin's estimates and thus add support to his theory.

Background

In 1958, A.W. Phillips published a paper that had studied the relationship between wage inflation and employment in the United Kingdom from 1861 to 1957. What he found was a consistent positive relationship: When employment was low, wages increased slowly, and when employment was high, wages rose quickly. His reasoning was that when demand for labor is high and there are “very few unemployed we should expect employers to bid wage rates up quite rapidly, each firm and each industry being continually tempted to offer a little above the prevailing rates to attract the most suitable labour from other firms and industries” (Phillips, 1958). And then on the other side, when demand for labor is low and there are many people who are unemployed, “workers are reluctant to offer their services at less than the prevailing rates” (Phillips, 1958), and thus wage rates fall only very slowly.

This relationship between unemployment and inflation was stable in the United States during the 1950s and 60s, but since then, the relationship has become less clear. An article from the St. Louis Federal Reserve states that in recent decades, “While the unemployment rate has declined …, inflation has remained low…This suggests that the Phillips curve has flattened” (Engemann, 2020). This assessment appears to be true as seen in Figure 1 where the relationship between Log Inflation and Employment is essentially non-existent, being only slightly positive. One theory from Federal Reserve Chair Jerome Powell for why this flattening has occurred is because “inflation expectations are so settled, and that’s what we think drives inflation” (Engemann, 2020). Another theory from Fed Vice Chair Richard Clarida is that “price inflation appears less responsive to resource slack” (Engelmann, 2020). But no matter the reason, experts seem to agree that “the relationship between unemployment and inflation has become very hard to spot” (Engelmann, 2020).

Figure 1. The Relationship between Inflation and Employment for the Years 1964-2023.

Note: Here the natural logarithm of the change of CPI (the price level) is represented on the Y-axis. The employment rate as a percentage of total labor force in the capitalist sector is represented on the X-axis.
Source: Author's calculations from FRED data.

Stephen Marglin disagrees with the above analysis. In particular, he outlines a long-run macroeconomic theory which preserves the fundamental relationship of the Phillips Curve. In the following paragraphs, we will provide necessary but insufficient background information on Marglin's long run macroeconomic theory.

To understand this theory and the regression, we need to understand labor. In Marglin's view, the capitalist economy represents only a fraction of the entire economic system. In parallel to the capitalist sector, there is a household sector where wage labor is minimal and production goes towards the satisfaction of wants and needs, not by the market economy. There is also a family enterprise sector where production is oriented towards the capitalist sector, but labor is supplied by non-wage earning family members and the rest of the world through immigration. Therefore, the flow of labor in between the capitalist sector and those external to it is determined by conditions within the capitalist economy. When conditions are fair, labor will tend to move from external sectors to the capitalist labor force. The real wage that represents workers' monetary demands is an important factor in determining labor movement. In Marglin's model, however, the real wage in the capitalist economy is endogenously determined. Other conditions that factor into the real wage are output and changes in the nominal price level. This split determination, although complicated, is used by Marglin to explain periods like the Great Depression where wages remain stable even though unemployment increased.

Initially, capital growth is determined by investment which is given by the interest rate not by output, wages or profitability. Savings is a constant fraction of income. It is assumed that saving is constant irrespective of income, so redistribution has no real impact on consumption, savings, or the real wage. This is inconsistent with the behavior of the labor and capital owning class, so Marglin's introduces the Cambridge Savings Theory into his model in which profit recipients save more than workers. Clearly, if labor consumes more than the capital owning class, increasing the amount of income given to laborers will increase demand while potentially decreasing investment. This idea is complicated, however, because market conditions will determine whether capital widening (capitalists invest to expand output) or capital deepening (capital investment substitutes capital for labor), is implemented.

The basic relationship between labor and capital illustrated above constitute the main theoretical divergence in Marglin's theory. His formal theory is not laid out in this paper because it is too complex and would warrant many more pages than are allowed.

The models presented in the text, though, converge on one point: positive demand shocks represented by increases in investment demand or reduction in desired savings. These are supposed to lead to an increase in employment and an increase in inflation which means the theory argues that the Phillips curve should be reflected in the data. Beyond this prediction, the models suggest that there are a variety of plausible responses to supply shocks. Both a negative association between inflation and employment (anti-Phillips stagflation) and a positive association (the Phillips relationship) are possible. These differing reactions to supply shocks stem from a key insight made by Marglin, that wage and price shocks have different effects on long-run aggregate demand and supply. These differences are captured in Marglin's models and describe how wage, price, and employment dynamics which constitute supply are determined by the interaction between aggregate demand, profit maximization, and the conventional or target wage level.

That is to say that these theories do assert that there is a tradeoff between employment and output on one hand and inflation on the other in both the short and long run. Higher output due to greater demand must be paid for with higher inflation as all classical theories suggest. What is new in Marglin's theory is that the rate of inflation associated with a given level of demand is dependent on the supply of goods and labor, modeled by Marglin as the price of energy and the level of the conventional wage. The elements in this theory are sufficient to explain the flattening or broken relationship between unemployment and inflation.

Empirical Section

Our sample is composed of 230 quarterly periods between the years 1964 and 2023, sourced from Federal Reserve Economic Data. To find the relationship between wage inflation and price inflation, we employed a two-stage regression technique. The first stage models the dependence of wage change on the distance (this is a dynamical model) from the conventional wage share, on unemployment, productivity growth, and change in energy prices. The second stage describes how price inflation depends on wage inflation, a stand in for labor supply in Marglin's complicated model of labor across sectors, productivity growth, and energy-price change (again representative of supply shocks).

In further detail, the first stage runs the the percentage change in nominal wages (dAvgHErn) on the labor share of output lagged one year (L4.LbrShr), the percentage change in output per employee hour (dOutperH), the percentage change in price of energy (dEngergy57), and the unemployment rate (UNRATE) as independent variables. We also included three dummy variables for 1970, 1994, and 2020, in which 0 indicates the period is prior to that year and 1 indicates the period is either in that year or later. These three years represent shifts in political power that affected the wage of workers and thus the supply of labor and aggregate supply which in turn impacts the Phillips relationship. The regression also controls for seasonality in the four different quarters of the year as well as a linear time trend. This regression is used to find the predicted values of the percentage change in nominal wages which is then used as an independent variable for the second stage.

The dependent variable for the second-stage regression is the percentage change in the CPI (dCPI), and the independent variables are the predicted values of the first-stage regression and again the percentage change in output per employee hour (OutperH) and percentage change in the price of energy (Energy 57). This regression also controls for seasonality and a time trend. The regression approach we are taking is a time-series approach, and thus, we tested all variables for unit roots and found none. Furthermore, we checked for serial correlation and heteroscedasticity and found that we could not reject the possibility of either, and thus both regressions are also run with Newey-West standard errors of a lag of two years.

Table 1. Descriptive Characteristics of Quarterly Periods from 1964-2023

Variable	Mean	Std. Dev.
dCPI	.0097	.0078
dAvgHErn	.0103	.0054
dAvgHErn_new	.0104	.0035
dOutperH	-.6131	5.887
dEnergy57	.0116	.0418
UNRATE	5.938	1.734
LbrShr	-.0772	4.043

Source: Author's calculations from FRED data.

Regression Results

In the first-stage regression, the only three variables that were statistically significant using Newey-West standard errors were a slightly negative time trend and two dummy variables for 1970 and 2020. The regression reveals that, on average, periods in 1970 or later had an average change in hourly earnings that was 0.53 percentage points larger than periods before 1970, holding all else constant. Furthermore, on average, periods in 2020 or later had an average change in hourly earnings that was 1.03 percentage points higher than periods before 2020, holding all else constant. Thus, not only does Marglin's theory that in 1970 political power shifted in favor of laborers and employees to increase their wages remain intact, but our hypothesis that a similar shift happened in 2020 due to changes in the labor market from the global pandemic is also supported. Although the results that the distance from the conventional wage share (L4.LbrShr), productivity growth (dOutperH), the change in energy prices (dEnergy57), and the unemployment rate, all do not statistically significantly impact the change in wages is not encouraging, the main goal of this regression was to retrieve the variation of wage inflation that is determined by these variables to then be used as an independent variable for the second-stage regression.

Table 2. 1st-Stage Regression: Estimated Impact of Selected Variables on Average Hourly Earnings

VARIABLES	(OLS) dAvgHErn	(Newey) dAvgHErn
L4.LbrShr	-0.0000	-0.0000
	(0.0001)	(0.0001)
dOutperH	-0.0001**	-0.0001
	(0.0000)	(0.0001)
dEnergy57	0.0048	0.0048
	(0.0069)	(0.0120)
UNRATE	-0.0002	-0.0002
	(0.0002)	(0.0002)
DUM1970	0.0053***	0.0053**
	(0.0013)	(0.0022)
DUM1994	0.0015	0.0015
	(0.0013)	(0.0023)
DUM2020	0.0103***	0.0103***
	(0.0014)	(0.0016)
q1	-0.0001	-0.0001
	(0.0008)	(0.0006)
q2	0.0001	0.0001
	(0.0008)	(0.0006)
q3	-0.0005	-0.0005
	(0.0008)	(0.0005)
t	-0.0001***	-0.0001***
	(0.0000)	(0.0000)
Constant	0.0147***	0.0147***
	(0.0013)	(0.0017)
Observations	230	230
R-squared	0.422	

Source: Author's calculations from FRED data.

The regression coefficients for the second-stage regression are more promising. Values for the predicted change in average hourly earnings (dAvgHErn_new), change in output per hour (dOutperH), and the change in energy prices (dEnergy57) were all statistically significant after performing Newey-West standard errors. The results show that on average an additional percentage point increase in the predicted change of average hourly earnings is associated with a .9133 percentage point increase in inflation, ceteris paribus. It's 95% confidence interval [0.4506, 1.3759] is in line with both Marglin's estimate of 0.7465 and with his overarching theory which states that the coefficient should be exactly equal to one.

Next, the results also show that on average an additional percentage point increase in the change of energy prices is associated with a .1095 percentage point increase in inflation, ceteris paribus. Its 95% confidence interval [0.0853, 0.1335] is also in line with Marglin's theory and estimate of .0925. Lastly, we found that on average an additional percentage point increase in productivity growth is associated with a .0002 percentage point increase in inflation. Its 95% confidence interval [0.00004, 0.00026] is not in line with Marglin's theory and regression result of -0.4043.

Our regression results for change in average hourly earnings and change in energy prices corroborate a key aspect of Marglin's theory. Namely, labor which is endogenously determined by the target wage and labor political power and energy prices, which constitutes a goods supply, are responsible for shifting the Phillips Curve.

Table 3. 2nd-Stage Regression: Estimated Impact of Selected Variables on Inflation

VARIABLES	(OLS) dCPI	(Newey) dCPI
dAvgHErn_new	0.9133***	0.9133***
	(0.1351)	(0.2348)
dOutperH	0.0002***	0.0002***
	(0.0001)	(0.0001)
dEnergy57	0.1095***	0.1095***
	(0.0074)	(0.0123)
q1	-0.0003	-0.0003
	(0.0008)	(0.0005)
q2	-0.0004	-0.0004
	(0.0008)	(0.0006)
q3	0.0003	0.0003
	(0.0009)	(0.0005)
t	-0.0000	-0.0000
	(0.0000)	(0.0000)
Constant	-0.0001	-0.0001
	(0.0022)	(0.0036)
Observations	230	230
R-squared	0.674	

Source: Author's calculations from FRED data.

Conclusion

Even with an additional 12 years after Marglin's regression data stops, in general, we found coefficient values that are in line with Marglin's own coefficients as well as with his long-run macroeconomic theory. The results show that Marglin's theory does, in fact, still explain the supposed break-down of the Phillips Curve. Additionally, our hypothesis that 2020 was an important year for shifts in political power between capital and labor was validated by the positive statistically significant coefficient for DUM2020.

However, despite these great results, there were a couple weaknesses. For example, not all the coefficients came out statistically significant, especially in the first-stage regression. One possible reason for this is that we had to use larger-range imperfect variables instead of variables that could have been more accurate but did not go back in time far enough to be used. The Average hourly earnings variable we used only included non-supervisory roles instead of all workers because that variable only started in 2006, and instead of the global price of energy variable that began in 1992, we used the U.S. city average CPI for energy that started in 1957. Another possible reason for larger standard errors is that there were simply not enough observations, only 230. If we had been able to use monthly observations instead of quarterly, we could have had more degrees of freedom to obtain more significant results.

The only weakness in our second-stage regression seems to be that the coefficient on the percentage change in productivity was found to be statistically significantly positive while Marglin received a negative estimate. Marglin's theory states that an increase in productivity through capital deepening would eventually lead to a decrease in inflation, holding all else constant, and thus we do not believe our positive result is accurate, and instead there must have been a violation of one of our time-series assumptions.

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Public Housing's Marginal Tax on Earnings and Work Disincentives

Demolition of St. Louis' Pruitt-Igoe:
A public housing development with such high crime and vacancy rates that it became a nationally recognized symbol of public housing failure (J.S.)

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Microeconomic Public Policy Issues
Final Draft
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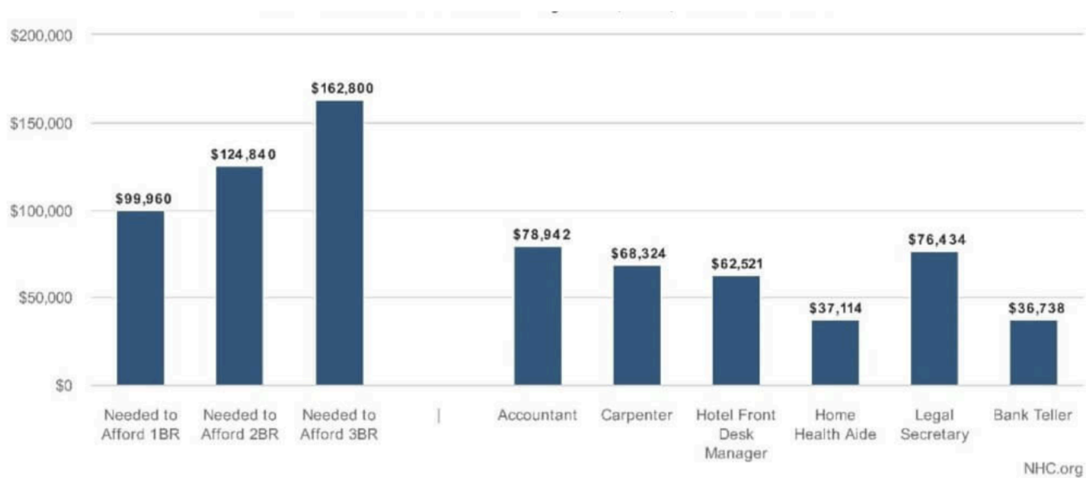
Introduction

In an effort to alleviate the financial burden on the nation's poorest households, the U.S. government provides housing assistance to low- and extremely low-income households. The Department of Housing and Urban Development (HUD), the government branch in charge of public housing, defines low-income households as those that earn less than 80 percent of the area median income (AMI), and extremely low-income households as those that earn less than 30 percent of the AMI. HUD gives priority to extremely low-income households; in 2016, 72 percent of housing assistance recipients met HUD's extremely low-income definition. Additionally, the average household in public housing earned $14,444 in 2016 (Docter), which lies about $1,500 below that year's federal poverty line for a two-person household ("2016 Poverty Guidelines"). Evidently, these households are deeply impoverished and struggle to afford market-rate rents. Thus, public housing is an essential government program in a nation where even hard-working Americans, as shown in Exhibit 1 below, struggle to afford housing (Dworkin). Five million low-income Americans currently benefit from housing assistance (Gartland), and an additional 4.4 million low-income Americans are on the waiting list to receive housing assistance. Many of these waitlists are closed to new applicants; therefore, the actual demand for public housing exceeds these figures ("Millions of Families"). In exchange for housing, unfortunately, many of these Americans will face deep stigmatization. Their home in "the projects" often assigns them an associated identity of crime, drug use, and laziness (Badger). Concerned with these stigmas, this paper will investigate whether or not housing assistance disincentivizes working. More specifically, it will examine the impact of associating public housing rental payments with a tenant's income and labor force participation.

Exhibit 1: Comparison of Income to Rental Market Prices in San Francisco-Oakland-Hayward, CA



[1]

It is important to note that Americans receiving housing assistance are traditionally obligated to contribute 30 percent of their income (after adjusting for specified allowances and deductions, such as childcare and healthcare) towards their rent. This payment is referred to as the total tenant payment (TTP) (Castells). Many critics scorn the current practice of calculating TTPs as a percentage of income rather than implementing a flat-rate rent, arguing that it serves as a marginal tax on earnings and disincentivizes work. However, others argue that the percentage model avoids unnecessarily placing an excessive rent burden on impoverished households. This paper will address the existing literature supporting both arguments after providing a brief history of public housing. Then, it will discuss two recent HUD studies Riccio et al. (2015) and Castells (2020) that changed TTP calculation methods to incentivize work among public housing tenants, both of which showed the changes to be unsuccessful. These studies instead point to external factors, such as psychological depression and burdensome child care, that impact the head of the household's ability to work. Given that personal circumstances pose a significant barrier to employment and improved earnings for public housing tenants, this paper concludes by

[1] https://nhc.org/two-issues-define-americas-new-housing-crisis/ 2 May, 2023 Acc.

arguing that HUD should prioritize policies that eliminate these barriers, rather than continuing to experiment with new TTP calculation methods.

History of Public Housing

The current public housing system is vastly different from Franklin D. Roosevelt's (FDR) vision for the Public Works Administration (PWA) housing program at its inception in 1933. Originally intended to create construction jobs and assist aspiring young homeowners in the wake of the Great Depression, government-sponsored housing was meant to be a temporary measure that benefited middle-income white Americans ("Public Housing"). The PWA did construct public housing units for African-American households, but these were isolated afterthoughts in far less desirable areas (Gross). Continuing with a vision of public housing for the middle class, FDR passed the National Housing Act of 1934, which created the Federal Housing Administration (FHA), now part of HUD. This legislation helped aspiring white homeowners by guaranteeing federal repayment of mortgages upon default ("National Housing"). This vision for public housing soon shrank, and by 1936 Congress dictated that PWA housing was exclusively for qualifying low-income American families (Martens). Then, the Taft-Ellender-Wagner Bill of 1937 created the United States Housing Authority, now HUD, as a federal agency that grants loans to local public housing authorities (PHAs) ("FDR and Housing"). Under this structure, local PHAs receive funding from HUD to oversee their city's or town's housing assistance programs (HUD's "Q and A").

In the post-World War II era, the American public housing system became intertwined with the Civil Rights Movement[2]. As the post-war economy boomed, large numbers of vacancies

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[2] Americans commonly accept a narrative of de facto segregation. Meaning, we place the blame of our nation's history of racist housing policy on individual private activity, such as white homeowners personally refusing to sell their homes to African Americans, rather than on the government. Richard Rothstein's *The Color of Law: A*

opened in white developments that were not filled by eligible African-Americans, since homeowners and PHAs could legally include racial covenants in their deeds prior to the Fair Housing Act of 1968. These racial covenants greatly limited public housing opportunities for African-Americans, resulting in long wait lists at non-white public housing developments (Gross). Other common racial housing discrimination tactics, such as redlining–the refusal of banks to grant mortgages for homes in predominately African-American neighborhoods–only further limited their housing options (Jackson). With the Fair Housing Act, African-American families were finally permitted to fill vacancies in white developments[3]. “White flight” ensued, marking the beginning of public housing’s decline in providing a high quality of life (Gross).

However, the modern reputation of public housing as government-funded slums is primarily attributable to the 1969 Brooke Amendment to the National Housing Act, which limited TTPs to 25 percent, later raised to 30 percent. Prior to the Brooke Amendment, public housing units had standard monthly rental rates that were not adjusted based on income. PHA’s could thus set rent to the amount necessary to maintain developments to a livable standard, which was often above 25 to 30 percent of a tenant’s income. Although well-intentioned, the Brooke Amendment greatly reduced PHAs’ budgets, making it difficult to maintain housing units at a livable standard. This combination of white flight and underfunded PHAs ensured

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Forgotten History of How Our Government Segregated America (2017) persuasively argues that instead government policies allowed for discriminatory housing practices that created de jure (government) segregation. He combines stories of those personally impacted by racist zoning ordinances with historical analysis to establish the government’s role in creating racially segregated neighborhoods that persist today, arguing that our government is obligated to reverse the generational impacts of its racist housing policies (Rothstein).

[3] While these policies have been reversed, the segregated neighborhoods created by them persist. This phenomenon is exemplified by Detroit, which is 80 percent African-American while Grosse Pointe, a nearby suburb, is 90 percent white (Semuels). Additionally, these racist housing policies created continuing political and social damage that extends beyond housing. For instance, the GI Bill helped returning World War II (WWII) veterans by funding the education of 8 million white Veterans and backing the home loans of 4.3 million white Veterans. These benefits, however, were unjustly denied to the 1.2 million African American WWII Veterans. The GI Bill thus advanced the education and housing of white Veterans, which allowed their families to accumulate generational wealth. By not extending these benefits to African American WWII Veterans, the GI Bill furthered the U.S. racial wealth gap of almost $30,000 today (Blakemore).

public housing's failure (Husock, "How Brooke"). The New York City Housing Authority (NYCHA), which operates 174,000 units as the nation's largest housing authority, is a perfect example of these failures. The agency is underfunded and its employees overworked, forcing the NYCHA to delay maintenance, repairs, and renovations that would now cost up to $30 billion. Their units are also marked by mold, water leaks, and rat infestations (Husock, "Ending NYCHA's").

Today, five million low-income Americans receive housing assistance, ninety percent of whom live in one of three arrangements: traditional public housing, Section-8 Housing Choice Vouchers (HCVs), or Section-8 Project-Based Vouchers (PBVs) (Gartland). The HCV program allows recipients to live in privately-owned units of their choosing with their PHA paying the difference between fair market rent (FMR) and their TTP ("Section 8"), whereas PBVs allow recipients to live at privately-owned developments that have designated certain units as affordable. Thus, HCVs and PBVs are almost identical; however, HCV vouchers belong to the tenants while PBVs belong to the unit (Fandel). All three of these predominant types of housing assistance use the 30-percent-of-income rent model (Riccio).

Evidence that the Current TTP Calculation Method Disincentivizes Working

General microeconomic theory suggests that correlating TTPs with income disincentivizes work. Specifically, multiple economic studies utilizing the concepts of the income and substitution effects have argued for housing assistance to disincentivize work. First, the income effect asserts that when tenants first receive housing assistance, their monthly rent expense decreases. Given that rent is a major expense for most households, especially those living in poverty, this decrease in rent increases the household's disposable income. Thus, tenants could maintain or even increase their standard of living while working less, suggesting that housing assistance is inherently a work disincentive. Additionally, the substitution effect asserts that the program's 30-percent marginal tax on income[4] disincentivizes working by lowering the return on earnings-per-hour-worked, introducing an incremental marginal tax increase from zero to 30 percent once a household receives public housing assistance (Castells).

Opponents of the current TTP calculation method also emphasize public housing's role in a larger welfare system that only further decreases employment incentives. Painter (2001) details the relationship between public housing and other welfare programs: housing assistance is a unique welfare program, since households not only pay to participate but pay a varying amount to do so. As a result, overconsumption can occur, as public housing tenants often are assigned units that exceed their spatial needs. Furthermore, housing is a complement to leisure, which suggests housing assistance would negatively impact employment and earnings more than other welfare programs. Additionally, many households simultaneously partake in welfare programs, as illustrated in Exhibit 2 below. Jaramillo, Rohe, and Webb (2020) further emphasize this point, explaining that households that increase their income face the potential of losing welfare eligibility, making it difficult for them to justify doing so.

[4] For comparison, the federal marginal tax on earnings ranged from 10 to 37 percent of taxable income in 2022 (Washington).

Exhibit 2:
Multiple Program Participation of Female-Headed Households Between the Ages of 16 and 15, Full Sample (N=692)

Program Participation	Current Housing Recipient	Waiting List	Housing Participant
AFDC only	0	0	0
Food stamps only	2	2	4
Medicaid only	1	2	3
AFDC and food stamps	0	0	0
AFDC and Medicaid	3	6	9
Food stamps and Medicaid	13	7	20
AFDC, food stamps, and Medicaid	13	5	18
Number of households participating in housing and at least one entitlement	32	22	54

Source: Tabulations of the 1984 SIPP 4th wave.
Note: This table is compiled from the sample of the 1984 SIPP cross-section used in the estimation. Housing participants include both current recipients of subsidies and those who are on the waiting list. In addition to the number of people who participate in housing represented in the table, there are 57 (5 on a waiting list) who do not participate in AFDC, food stamps, or Medicaid. A total of 227 participate in at least one of the four programs.

Additionally, Husock (2019, "Ending NYCHA's") explains how the Housing Authority's mismanagement and ulterior motives have created work disincentives in NYCHA. He explains how the PHA's shortcomings have created a dependency trap, which is demonstrated by the low exit rate of public housing tenants in New York City. As shown in Exhibit 3, almost half (47 percent) of the households receiving assistance from NYCHA have done so for over twenty years. This trend shows that in many cases public housing is not serving as temporary assistance, but rather as a long-term safety net. Husock argues that if housing assistance remains a permanent option for households, then they face minimal pressure to increase their earnings.

Exhibit 3:
How Long New York City Tenants Remain in Public Housing

Tenure	Number of Households	Percentage of Households
Up to 5 Years	24,828	15%
5–10 Years	24,011	14%
10–20 Years	41,611	24%
20–30 Years	31,580	18%
30–40 Years	18,107	11%
Over 40 Years	30,596	18%
Total	170,733	

Source: NYCHA, Performance Tracking and Analytics Department, Tenant Data System 2019

Husock's research also found that in some cases, NYCHA actually benefited from tenants receiving housing assistance for prolonged periods. The Authority was able to boost its earnings by establishing flat rate rents for its higher-earning tenants, as permitted by Congress in 1989. These tenants would have otherwise been replaced by new tenants paying a lower TTP, which would decrease the city's public housing budget even further. As a result, in 2006, 54 thousand NYCHA households that earned 60 percent or more of the AMI continued to receive housing assistance at one of three flat rate rents dependent on their income level. In 2014, the federal government changed flat rate rent laws so that all tenants paying a flat rate rent paid the same one. Many of these households left public housing as a result, and in 2019 only 9.5 thousand households continued to pay a flat rate rent. The existence of flat rate rents, however, proves that housing authorities can easily prioritize their bottom lines above improving tenant outcomes, which is likely partially responsible for public housing being a system that Husock believes "encourages multi-generational poverty."

Castells (2020) also provides empirical evidence that public housing's marginal tax on earnings disincentivizes work. It discusses Mills et. al. (2006)'s important study that compared labor outcomes for households on the housing assistance waitlist already receiving Temporary Assistance for Needy Families (TANF) benefits. They found that once families received HCVs they worked less, but only during the first year of random assignment. Jacob and Ludwig (2012) found that the Chicago Housing Authority's 1997 lottery resulted in negative labor supply impacts, as subsidy recipients reduced their employment by six percent and reduced their quarterly earnings by 10 percent. Finally, Gubits et al. (2015)'s Family Options Study offered housing vouchers to homeless families. They concluded that voucher recipients reduced their employment by 11 percentage points in comparison to the control group. This difference was more drastic at first and was reduced to six percentage points after three years.

Thus, the critics of the current TTP calculation method point to the income and substitution effects, a larger welfare trap, housing assistance's dependency trap, and empirical evidence as evidence of its work disincentives.

Evidence of External Barriers to Employment Impacting Labor Force Outcomes for Public Housing Tenants

Conversely, others argue that the current total tenant payment (TTP) method does not discourage public housing tenants to work, but rather that they face numerous personal barriers impacting their labor outcomes irrespective of their TTPs. For instance, Riccio et al. (2017)[5] suggest that many heads of households in public housing face external employment barriers.

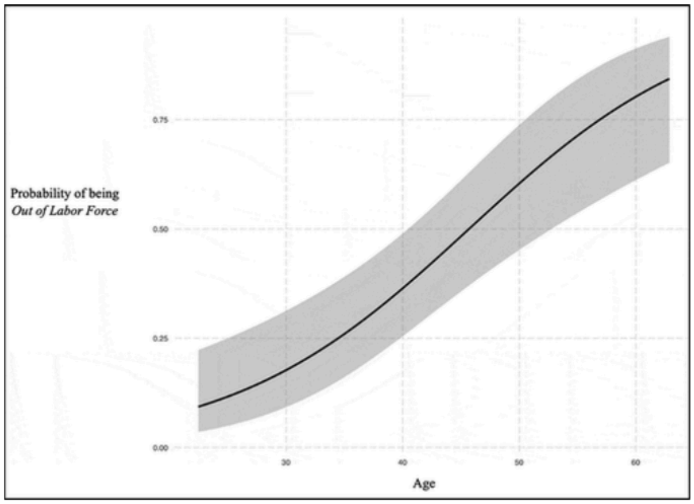
[5] See page 13 for an explanation of their research methods.

They found that more than half of their respondents faced an employment barrier, with health concerns (31 percent) and childcare responsibilities (21 percent) as the two largest. The study also found that caring for a sick or disabled family member was another significant barrier to employment, as it affected about 20 percent of participating families in their sample of San Antonio and Louisville households. These factors are entirely independent of the rental calculation method used by PHAs, meaning that a large share of public housing tenants' ability and motivation to work would not change if their rent were increased or standardized.

Jaramillo, Rohe and Webb (2020) also found that external barriers to employment were crucial determinants of labor force participation for heads of households receiving housing assistance. They collected data through a survey of nondisabled and nonelderly Charlotte Housing Authority (CHA) tenants and analyzed demographic differences between nonemployed heads of households who either were or were not seeking work[6]. The researchers ran a regression to analyze the demographic difference between the two nonemployed groups and observed statistically significant differences in age,[7] as shown in Exhibit 4 below.

[6] The researchers used the commonly-accepted definitions of labor force participation.
[7] Note that their sample of 335 CHA public housing residents was 98 percent African-American and 96 percent female, so the only varying demographic the researchers were able to analyze was age.

Exhibit 4:
Probability of Being Out of the Labor Force as Age Increases



They found that non-employed[8] tenants were older; less likely to have continued their education beyond high school or a GED; less likely to have completed at least one job training program; and less likely to be enrolled in education courses at the time of the survey. They also found that heads of households in their sample not looking for work were more likely to have depression and health problems. Interestingly, unemployed heads of households with children were more likely to be in the labor force than those without children[9]. Their research also revealed structural barriers to employment, such as limited nearby work opportunities and lack of access to transportation. Thus Jaramillo, Rohe, and Webb's findings show that multiple factors beyond the TTP's marginal tax on earnings impact a public housing tenant's willingness to work. Both Riccio et al. (2017) and Jaramillo, Rohe, and Webb (2020) suggest that work disincentives

[8] Here, non-employed takes on the widely accepted macro-economic definition of someone who is not working and not seeking work. This definition is not to be confused with unemployed, which, in macroeconomic terms, describes someone who is not working but is actively seeking work or is temporarily laid off (Murphy).
[9] This finding does not contradict the notion that child care is a frequent barrier to employment for public housing tenants. Householders with children have greater expenses than those without children and thus are naturally inclined to work more to cover these greater expenses. So, while heads of households with children are more motivated to work, doing so can be complicated, since it requires them to find supervision for their children.

in public housing likely extend far beyond the reach of the TTP. In reality, many households face serious barriers to employment that make them unable to work. These households would thus be unfairly penalized if PHAs were to establish punitive work requirements.

HUD's Recent Experimentation with the TTP Calculation Method

The Rent Reform Demonstration

Recognizing the arguments on both sides of the question, HUD has launched a series of experimental trials to determine if alternative total tenant payment (TTP) calculation methods would increase labor outcomes. Riccio et al. (2015)'s study labeled *The Rent Reform Demonstration* (RRD) experimented with Housing Choice Vouchers (HCVs) to determine if decreasing TTP's sensitivity to changes in income would simultaneously alleviate public housing's two largest challenges, work disincentives and immense administrative burdens, without imposing unnecessary financial hardship on households. These goals were meant to be accomplished without increasing the average cost of the voucher program per family served.

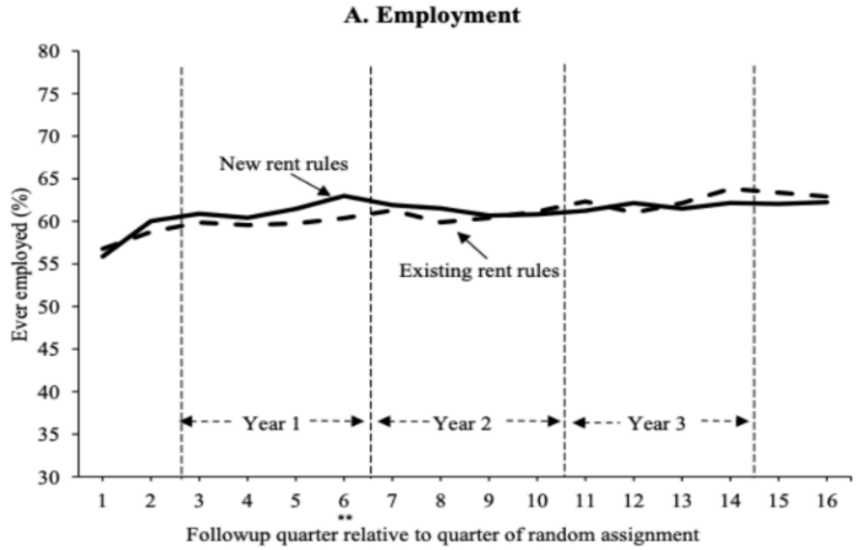
The most relevant change under the new rent rules is the switch from an annual to a triennial TTP recertification. Tenants could still, however, report decreases in income between certification periods. The researchers hoped that extending the recertification period would incentivize tenants to increase their incomes, since the marginal tax of 30 percent on increased earnings would be temporarily avoided. A longer certification period also meant that underfunded and overworked PHAs could dedicate less time and resources towards recertifications, one of their most demanding tasks. The new rent rules under the RDD were more nuanced than simply extending the recertification period. The current policy of establishing rent at 30 percent of a household's current or anticipated income was modified to 28 percent of a household's retrospective gross income and eliminated allowances and deductions. The new formula also ignored household income generated by assets valued below $25,000. It also established or raised a minimum rent and simplified the method of calculating utility allowances.

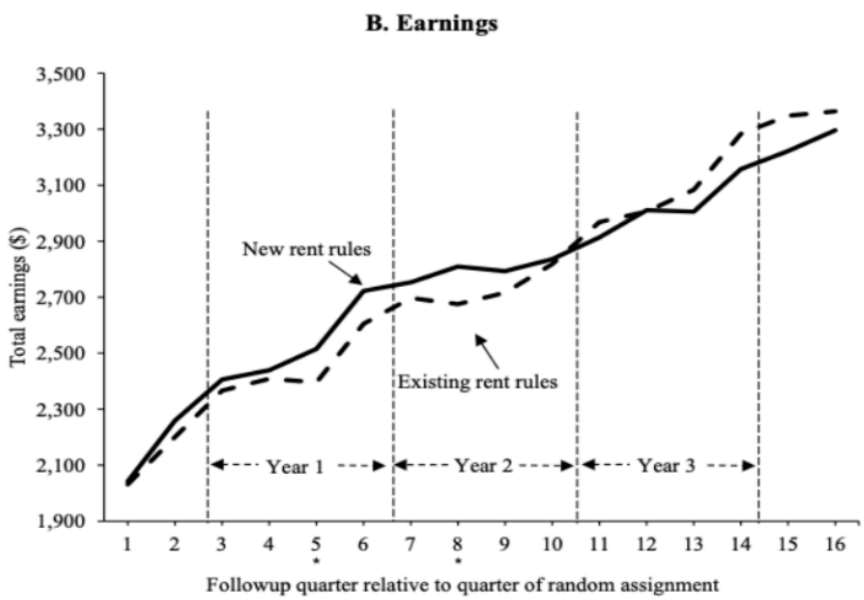
The study analyzed the impact of these changes on 6,665 households over a six-year period across four PHAs: the Lexington-Fayette Urban County Housing Authority in Kentucky, the Louisville Metropolitan Housing Authority in Kentucky, the District of Columbia Housing Authority in Washington, D.C., and the San Antonio Housing Authority in Texas. These PHAs belong to a subset of 39 PHAs participating in HUD's Moving to Work (MTW) demonstration, which allows PHAs the flexibility to change rent rules without seeking formal approval. Eligibility within the PHAs was limited to households approaching their certification period in early 2015 and whose head was not defined as senior or disabled.

When analyzing the results, it is essential to consider specific circumstances in Louisville and Washington, D.C. that affected the study. Families assigned to the new rent rules group in Louisville could opt-out and return to the existing rent rules group; 22 percent of these households took advantage of this option. For evaluation purposes, these opt-out participants remained in the new rent rules group to avoid bias. Thus, not all members of the Louisville new rent rules group were exposed to the changes, prompting the researchers to provide adjusted supplementary estimates. Results from Washington, D.C. are also subject to potential bias, since the district's PHA switched its existing program to a biennial recertification period, which makes it difficult to evaluate the impact of extending the recertification period. Additionally, the PHA withdrew prematurely from the study in September 2019. Given these changes, the pooled results from the RRD are often provided with and without Washington, D.C..

The authors found on average that prolonging the recertification period from one to three years did not have a significant impact on labor outcomes. Exhibit 5 illustrates the similarity of outcomes between the two groups. Employment for both groups remains relatively stable between fifty-five and sixty-five percent throughout the duration of the study. Similarly, earnings across the two groups increase at a similar rate. These data suggest that temporarily removing the marginal tax on additional income does not incentivize working. Participants were aware that their TTPs would be recalculated at the conclusion of the triennial recertification period, which should cause them to behave differently than if their rent payments became permanently uncorrelated with changes in their income. Thus, these results can only allow us to speculate that results would be similar if HUD's marginal tax on additional income was removed entirely. While the temporary switch from an annual to triennial recertification did not incentivize working, PHAs should still consider adopting the triennial recertification model to lower their spending and reduce their administrative burden.

Exhibit 5:
Quarterly Impacts on Employment and Earnings Within First 42 Months of Followup: Lexington, Louisville, San Antonio Combined, Heads of Households





Notes: Quarter 1 is the quarter of random assignment. Estimates were regression-adjusted using ordinary least squares, controlling for pre-random assignment characteristics of sample members. Rounding may cause slight discrepancies in calculating sums and differences. A two-tailed t-test was applied to differences between research groups. The p-value indicates the likelihood that the difference between the new rent rules group and the existing rent rules group arose by change. Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; and * = 10 percent. Sample sizes for specific outcomes may vary because of missing values.
Source: MDRC calculations using quarterly wage data from the National Directory of New Hires

Exhibit 6 further emphasizes the failure of the RRD to incentivize work: comparing the new and existing rent rules groups, the percent of heads of households ever employed across all PHAs varies by just 0.01 percentage points. Similarly, the total earnings for the full period across all PHAs were found to be $41,074 for the new rent rules group and $41,046 for the existing rent rules group, just a $28 difference across a 42-month period. When Washington, D.C. is removed from the data set, the results are almost identical. The percentage of heads of households who were ever employed varies by just 0.06 percentage points and full-period earnings differ by just $7.

Exhibit 6:
Impacts on Employment and Earnings Within 42 Months of Followup:
Heads of Households

Outcome	New Rent Rules	Existing Rent Rules	Difference (Impact)		P-Value
All PHAs					
Ever employed (%)					
Year 1 (quarters 3–6)	68.1	66.9	1.2		0.180
Year 2 (quarters 7–10)	68.0	67.9	0.2		0.859
Year 3 (quarters 11–14)	68.2	68.1	0.1		0.919
Quarter 15	58.8	59.4	– 0.6		0.577
Quarter 16	58.4	58.4	0.0		0.989
Full period (quarter 3–16)	78.9	78.8	0.1		0.905
Average quarterly employment[a] (%)					
Year 1 (quarters 3–6)	55.8	54.6	1.3	*	0.095
Year 2 (quarters 7–10)	58.1	57.3	0.7		0.415
Year 3 (quarters 11–14)	58.7	58.9	– 0.2		0.792
Full period (quarter 3–16)	57.6	57.2	0.5		0.523
Total earnings ($)					
Year 1 (quarters 3–6)	10,133	9,973	159		0.415
Year 2 (quarters 7–10)	11,747	11,486	260		0.294
Year 3 (quarters 11–14)	12,663	12,886	– 223		0.428
Quarter 15	3,379	3,477	– 97		0.246
Quarter 16	3,369	3,417	– 47		0.578
Full period (quarter 3–16)	41,074	41,046	28		0.970
Sample size (total = 6,665)	3,312	3,353			

Outcome	New Rent Rules	Existing Rent Rules	Difference (Impact)	P-Value
Lexington, Louisville, and San Antonio Combined				
Ever employed (%)				
Year 1 (quarters 3–6)	72.7	71.4	1.2	0.232
Year 2 (quarters 7–10)	71.5	71.8	– 0.3	0.775
Year 3 (quarters 11–14)	72.0	72.3	– 0.3	0.781
Quarter 15	62.0	63.4	– 1.3	0.285
Quarter 16	62.3	62.9	– 0.7	0.604
Full period (quarter 3–16)	82.2	82.8	– 0.6	0.560
Average quarterly employment[a] (%)				
Year 1 (quarters 3–6)	61.4	59.9	1.6 *	0.093
Year 2 (quarters 7–10)	61.2	60.7	0.6	0.589
Year 3 (quarters 11–14)	61.7	62.3	– 0.6	0.571
Full period (quarter 3–16)	61.5	61.2	0.3	0.737
Total earnings ($)				
Year 1 (quarters 3–6)	10,047	9,737	311	0.160
Year 2 (quarters 7–10)	11,146	10,862	284	0.309
Year 3 (quarters 11–14)	12,014	12,301	– 287	0.355
Quarter 15	3,222	3,348	– 126	0.179
Quarter 16	3,296	3,364	– 68	0.485
Full period (quarter 3–16)	39,482	39,489	– 7	0.994
Sample size (total = 4,756)	2,368	2,388		

PHA = public housing agency.
[a]Average quarterly employment is calculated as the total number of quarters with employment divided by the total number of quarters of followup, expressed as a percentage.
Notes: Estimates were regression-adjusted using ordinary least squares, controlling for pre-random assignment characteristics of sample members. Rounding may cause slight discrepancies in calculating sums and differences. A two-tailed t-test was applied to differences between research groups. The p-value indicates the likelihood that the difference between the new rent rules group and the existing rent rules group arose by chance. Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; * = 10 percent. Sample sizes for specific outcomes may vary because of missing values.
Source: MDRC calculations using quarterly wage data from the National Directory of New Hires

Labor outcomes by PHA, however, showed both positive and negative impacts on employment and income, as shown in Exhibit 7. For instance, Lexington and San Antonio observed some positive outcomes under the new rent rules, but these findings were inconsistent and not statistically significant. In both cities, the new rent rules group out-earned the existing rent rules group in years two and three by a non-statistically significant margin. Additionally, the new rent rules group in San Antonio out-earned its counterparts by a less aggressive rate in year three as compared to year two. Interestingly, the positive impacts were less prevalent in the study's later years, suggesting that some households may have purposefully decreased their earnings in anticipation of their triennial recertification. However, the period directly approaching the recertification does not show a drop in earnings, which weakens this hypothesis. Nevertheless, these results offer the potential for triennial recertifications to incentivize work, but not on a large scale.

Exhibit 7:
Impacts on Employment and Earnings Within 42 Months of Followup,
By PHA: Heads of Households

Outcome	New Rent Rules	Existing Rent Rules	Difference (Impact)		P-Value	
Lexington						
Ever employed (%)						
Year 1 (quarters 3–6)	78.3	76.1	2.2		0.296	
Year 2 (quarters 7–10)	75.4	73.0	2.4		0.302	
Year 3 (quarters 11–14)	78.4	73.4	5.0	**	0.035	††
Quarter 15	69.4	64.1	5.3	*	0.052	††
Quarter 16	68.0	65.4	2.6		0.329	
Full period (quarter 3–16)	86.3	83.3	3.0		0.132	
Average quarterly employment[a] (%)						
Year 1 (quarters 3–6)	65.5	64.2	1.3		0.505	
Year 2 (quarters 7–10)	64.8	61.8	3.1		0.167	
Year 3 (quarters 11–14)	67.0	63.7	3.3		0.150	†
Full period (quarter 3–16)	66.2	63.4	2.7		0.134	
Total earnings ($)						
Year 1 (quarters 3–6)	10,204	10,102	102		0.827	
Year 2 (quarters 7–10)	11,346	10,489	857		0.145	††
Year 3 (quarters 11–14)	12,637	11,848	788		0.243	†
Quarter 15	3,291	3,369	– 77		0.702	
Quarter 16	3,359	3,275	84		0.667	
Full period (quarter 3–16)	40,791	39,039	1,751		0.330	
Sample size (total = 979)	486	493				

Outcome	New Rent Rules	Existing Rent Rules	Difference (Impact)		P-Value	
Louisville						
Ever employed (%)						
Year 1 (quarters 3–6)	71.9	72.1	– 0.2		0.903	
Year 2 (quarters 7–10)	71.9	73.4	– 1.6		0.377	
Year 3 (quarters 11–14)	71.4	74.9	– 3.5	**	0.048	††
Quarter 15	60.2	64.7	– 4.5	**	0.025	††
Quarter 16	61.5	63.5	– 1.9		0.337	
Full period (quarter 3–16)	81.5	83.3	– 1.8		0.233	
Average quarterly employment[a] (%)						
Year 1 (quarters 3–6)	60.9	59.6	1.2		0.412	
Year 2 (quarters 7–10)	60.7	62.3	– 1.7		0.303	
Year 3 (quarters 11–14)	61.7	65.2	– 3.5	**	0.039	†
Full period (quarter 3–16)	61.0	62.6	– 1.6		0.235	
Total earnings ($)						
Year 1 (quarters 3–6)	10,164	10,029	135		0.716	
Year 2 (quarters 7–10)	11,236	12,027	– 791	*	0.088	††
Year 3 (quarters 11–14)	12,314	13,646	– 1,333	***	0.009	†
Quarter 15	3,284	3,627	– 343	**	0.026	
Quarter 16	3,417	3,668	– 251		0.123	
Full period (quarter 3–16)	40,288	42,919	– 2,631	*	0.063	
Sample size (total = 1,908)	947	961				
San Antonio						
Ever employed (%)						
Year 1 (quarters 3–6)	70.7	68.2	2.5		0.139	
Year 2 (quarters 7–10)	69.3	69.4	– 0.1		0.953	
Year 3 (quarters 11–14)	69.6	68.7	0.9		0.635	††
Quarter 15	60.3	61.4	– 1.1		0.580	††
Quarter 16	60.6	60.3	0.3		0.892	
Full period (quarter 3–16)	81.3	81.4	– 0.2		0.926	
Average quarterly employment[a] (%)						
Year 1 (quarters 3–6)	60.0	57.8	2.2		0.145	
Year 2 (quarters 7–10)	59.8	58.4	1.4		0.408	
Year 3 (quarters 11–14)	59.1	58.5	0.6		0.723	†
Full period (quarter 3–16)	59.7	58.5	1.2		0.416	
Total earnings ($)						
Year 1 (quarters 3–6)	9,849	9,240	609	*	0.084	
Year 2 (quarters 7–10)	10,909	9,900	1,009	**	0.024	††
Year 3 (quarters 11–14)	11,341	11,194	148		0.768	†
Quarter 15	3,130	3,045	86		0.575	
Quarter 16	3,165	3,073	92		0.554	
Full period (quarter 3–16)	37,907	36,258	1,649		0.234	
Sample size (total = 1,869)	935	934				

Outcome	New Rent Rules	Existing Rent Rules	Difference (Impact)	P-Value
Washington, D.C.				
Ever employed (%)				
Year 1 (quarters 3–6)	56.7	55.4	1.2	0.459
Year 2 (quarters 7–10)	59.4	58.0	1.4	0.458
Year 3 (quarters 11–14)	58.9	57.9	1.1	0.576 ††
Quarter 15	51.0	49.4	1.7	0.386 ††
Quarter 16	49.1	47.0	2.1	0.284
Full period (quarter 3–16)	70.7	69.1	1.6	0.346
Average quarterly employment[a] (%)				
Year 1 (quarters 3–6)	41.9	41.4	0.5	0.703
Year 2 (quarters 7–10)	50.2	49.1	1.1	0.502
Year 3 (quarters 11–14)	51.2	50.4	0.8	0.650 †
Full period (quarter 3–16)	48.0	47.1	1.0	0.468
Total earnings ($)				
Year 1 (quarters 3–6)	10,285	10,620	– 335	0.408
Year 2 (quarters 7–10)	13,200	13,083	117	0.823 ††
Year 3 (quarters 11–14)	14,268	14,354	– 86	0.887 †
Quarter 15	3,768	3,799	– 31	0.859
Quarter 16	3,559	3,541	17	0.921
Full period (quarter 3–16)	44,920	45,041	– 121	0.940
Sample size (total = 1,909)	944	965		

[a]Average quarterly employment is calculated as total number of quarters with employment divided by total number of quarters of followup, expressed as a percentage.

Notes: Estimates were regression-adjusted using ordinary least squares, controlling for pre-random assignment characteristics of sample members. Rounding may cause slight discrepancies in calculating sums and differences. A two-tailed t-test was applied to differences between research groups. The p-value indicates the likelihood that the differences between the new rent rules group and the existing rent rules group arose by chance. Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; * = 10 percent. The H-statistic test was used to test for statistically significant differences in impact estimates across different subgroups. Statistical significance levels are indicated as: ††† = 1 percent; †† = 5 percent; † = 10 percent. Sample sizes for specific outcomes may vary because of missing values.

Source: MDRC calculations using quarterly wage data from the National Directory of New Hires

The RDD, however, had a negative impact on earnings in Louisville, with the control group out-earning the new rent rules group by a statistically significant margin of $2,631. The existing rent rules group was also more active in the labor market with an average quarterly employment rate of 62.6 percent compared to 61 percent. It is important to consider that 22 percent of the new rent rules group opted out but remained in the data set. This discrepancy might explain the negative outcomes in Louisville, but it is unlikely. The opt-out participants should have mirrored their control group counterparts, so it is possible that the opt-out participants instead raised the employment rate and earnings for the new rent rules group, and the negative impacts are even more dramatic than the data suggests. Overall, the inconsistent findings of the RRD suggest that PHAs' annual recertification does not disincentivize working.

The Santa Clara County Housing Authority's Response to Budget Cuts

Similarly, Castells (2020) analyzed the impact of increasing HCV recipients' TTPs on labor outcomes in Santa Clara, CA[10]. This study follows the Santa Clara County Housing Authority's (SCCHA) response to the 2013 federal budget cuts to the HCV program. By raising tenant rent contributions and adjusting the voucher size policy, the SCCHA responded to these budget cuts without any households losing assistance. The first policy change increased the tenant rent contribution from 30 percent of adjusted income (approximately 28 percent of gross income) to 35 percent of gross income. This switch meant that allowances and deductions for things like childcare and medical bills were no longer considered in TTP calculations. In 2014, when federal funding increased, the rent contribution was lowered to 32 percent of gross income.

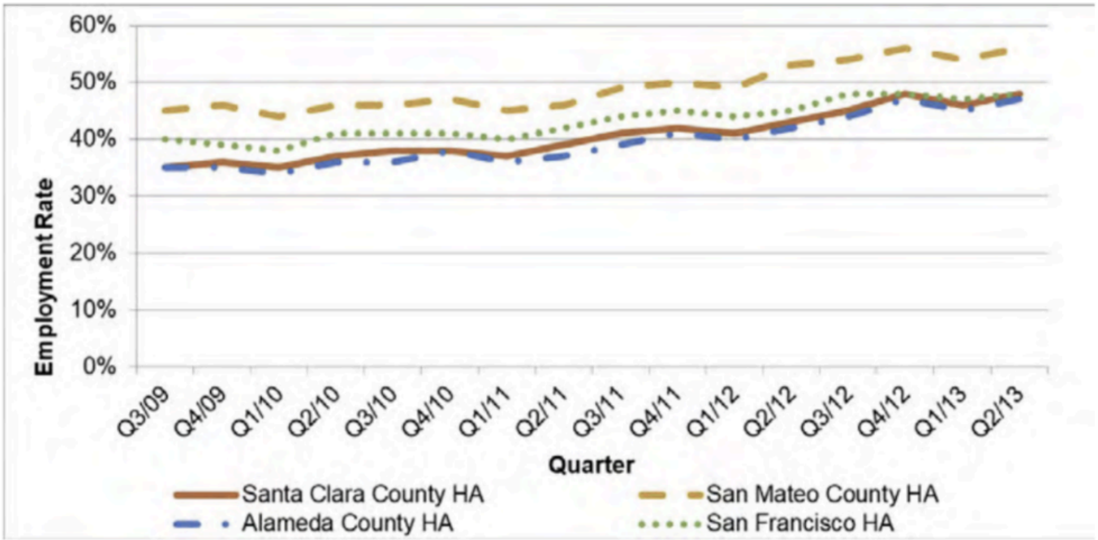
The second policy change decreased voucher sizes. Previously, households were allotted a bedroom for heads of households and their spouses, as applicable, plus a bedroom for each household member of different generations and sex, so long as the resident was over five-years-old. The policy change allocated a bedroom for the heads of households and their spouses, as applicable, and additional rooms for every two household members, regardless of

[10] The study only considers the labor impact on nondisabled, nonelderly individuals and households, since this demographic is most able to respond to the change

age, gender, or relation. Thus, this policy change left 17 percent of all SCCHA HCV households and 23 percent of its nonelderly, nondisabled households with smaller vouchers. All in all, these policy changes, which affected all SCCHA tenants, resulted in an approximate decrease in housing subsidies of $1,600 in year one, $1,550 in year two, and $1,330 in year three per household.

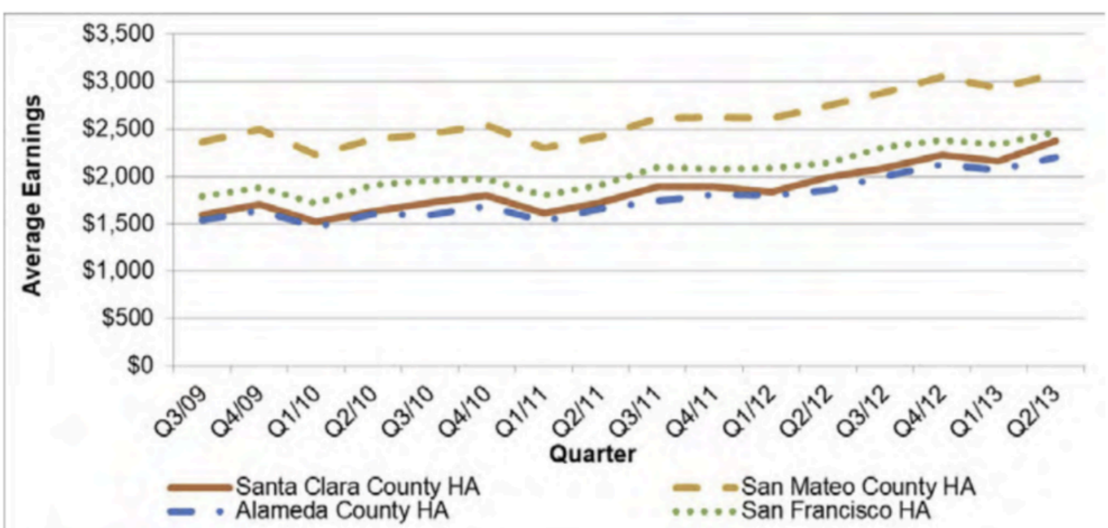
Next, Castell compared labor outcomes in Santa Clara to those of the Housing Authority of the County of Alameda, the Housing Authority of the County of San Mateo, and the San Francisco Housing Authority. The study ultimately found no improvements in earnings or employment among SCCHA tenants over the four-year follow-up period. As shown in Exhibits 8 and 9, SCCHA's quarterly unemployment rate and average earnings followed similar trends to its comparable PHAs. SCCHA's quarterly unemployment rate remained similar to Alameda's unemployment rate throughout the duration of the study and remained below San Mateo's and San Francisco's unemployment rate, except for some slight overlap between the unemployment rates of SCCHA and San Francisco in late 2012 and early 2013. Overall, however, SCCHA's unemployment did not change in comparison to similar PHAs that did not adopt the more demanding rent rules. Similarly, SCCHA's average quarterly earnings remain consistent with those of Alameda County's PHA and below those of San Mateo's and San Francisco's PHAs through the duration of the survey. The fact that SCCHA's unemployment rate and average quarterly earnings did not improve in comparison to the control PHAs suggests that increasing the TTP did not incentivize working.

Exhibit 8:
Baseline Trends in Quarterly Employment Rates of Nonelderly, Nondisabled Adults in SCCHA and Selected Comparison Housing Agencies



HA = housing authority.
Note: Sample consists of adults in the Housing Choice Voucher program who were not elderly or adults with disabilities.
Source: California Employment Development Department individual-level aggregate unemployment insurance data

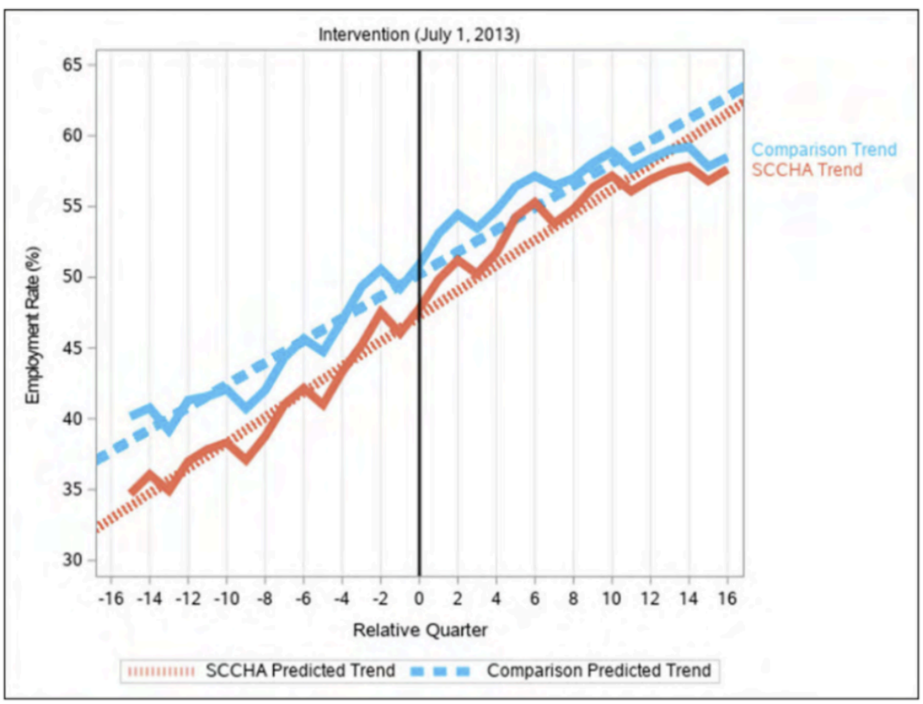
Exhibit 9:
Baseline Trends in Quarterly Earnings of Nonelderly, Nondisabled Adults in SCCHA and Selected Comparison Housing Agencies



HA = housing authority.
Notes: Sample consists of adults in the Housing Choice Voucher program who were not elderly and did not have disabilities. Earnings not adjusted for inflation.
Source: California Employment Development Department aggregate unemployment insurance data

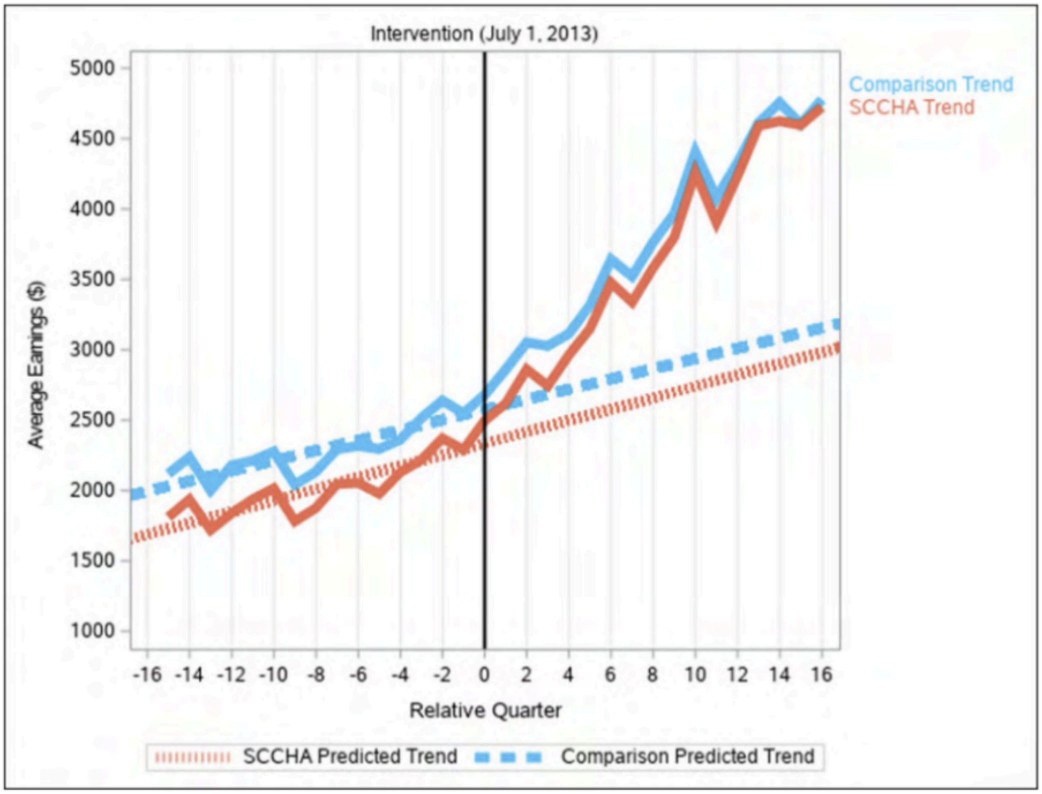
Exhibits 10 and 11 provide further insight into the shortcomings of the SCCHA rent reform to incentivize increased earnings. These figures compare the deviations of actualized employment rates and average earnings from predicted employment rates and average earnings for both SCCHA and a group of comparable PHAs. Further analysis revealed that neither group's actualized employment rates or average earnings deviated far enough from the predicted rates for them to be statistically significant. These findings further suggest that these policy changes did not incentivize working. Finally, Exhibit 12 shows only small and statistically insignificant increases in SCCHA's employment rate and earnings over the duration of the study. These findings further suggest that the rent reforms had no impact on labor market outcomes.

Exhibit 10:
Quarterly Employment Rates for Nonelderly, Nondisabled Adults in the Santa Clara County Housing Authority and Comparison Group



SCCHA = Santa Clara County Housing Authority.
Notes: Samples consist of adults who were not elderly and did not have disabilities. The set of comparison group public housing agencies includes the San Mateo County Housing Authority, the San Francisco Housing Authority, and the Alameda County Housing Authority. Impacts were estimated using a comparative interrupted time series model. Average quarterly earnings were adjusted for inflation to 2017 dollars using the Bureau of Labor Statistics Consumer Price Index.
Source: California Employment Development Department individual-level aggregate unemployment insurance data

Exhibit 11:
Average Quarterly Earnings for Nonelderly, Nondisabled Adults in the Santa Clara County Housing Authority and Comparison Group



SCCHA = Santa Clara County Housing Authority.

Notes: Samples consist of adults who were not elderly and did not have disabilities. The set of comparison group public housing agencies includes the San Mateo County Housing Authority, the San Francisco Housing Authority, and the Alameda County Housing Authority. Impacts were estimated using a comparative interrupted time series model. Average quarterly earnings were adjusted for inflation to 2017 dollars using the Bureau of Labor Statistics Consumer Price Index.

Source: California Employment Development Department individual-level aggregate unemployment insurance data

Exhibit 12:

Impacts on Average Quarterly Employment Rate and Annual Earnings of Nonelderly, Nondisabled Adults

Outcome	SCCHA Mean	Estimated Effect	Std. Error	P-Value
Employment Rate				
Year 1	50.8	-0.5	0.9	0.604
Year 2	54.5	0.0	1.2	0.972
Year 3	56.6	0.1	1.5	0.929
Year 4	57.5	0.1	1.8	0.941
Earnings				
Year 1	11,187	46	349	0.897
Year 2	13,549	143	474	0.763
Year 3	16,198	200	597	0.738
Year 4	18,538	509	725	0.484
Sample Size				34,075

SCCHA = Santa Clara County Housing Authority.

*Notes: Samples consist of adults who were not elderly and did not have disabilities. The set of comparison group public housing agencies includes the San Mateo County Housing Authority, the San Francisco Housing Authority, and the Alameda County Housing Authority. Effects were estimated using a comparative interrupted time series model. All estimated earnings effects are reported in 2017 dollars. The p-value indicates the likelihood that the estimated impact (or larger) would have been generated by an intervention with zero true effect. Statistical significance levels are indicated as: *** = 1 percent; ** = 5 percent; * = 10 percent.*

Source: California Employment Development Department individual-level aggregate unemployment insurance data

The Solution: Mixed-Income Housing

Based on the failure of the Rent Reform Demonstration and SCCHA's experimentation with the TTP calculation to increase labor force participation, it is likely that the Department of Housing and Urban Development (HUD) must look to experimental measures beyond rental calculations to create better outcomes for its tenants. This point is further emphasized by the overwhelming evidence that public housing tenants face both personal and structural external barriers to employment, many of which could be possibly eliminated through government programs.

Recognizing these issues, HUD launched the Rental Assistance Demonstration (RAD) in 2013 in an attempt to increase wellbeing and prosperity for its tenants and to better utilize its economic resources. This program promotes public-private partnerships, so that private developers can assume management of existing public housing developments or construct new developments with a portion of units designated as affordable. Tenants in these units receive Housing Choice Vouchers (HCVs), so that tenants pay their TTP directly to the landlord, and the PHA guarantees the remaining housing assistance payment. This system allows PHAs to provide housing units to low-income families without being responsible for maintenance, and thus more efficiently allocate their budgets. Additionally, developers benefit from participating since they are guaranteed rent by the federal government, against which they are able to borrow. Hence, this program has proven largely successful for both developers and PHAs.

RAD has allowed for the gradual emergence of mixed-income housing, an affordable housing solution that allows low-income tenants to live alongside market-rate tenants in identical units. Under the traditional mixed-income housing model, a development designates units as low-income, affordable, and market-rate. Low-income families receiving housing assistance use their HCVs to then live in a housing development alongside market-rate tenants, and are no longer stigmatized by the shortcomings of public housing that can affect work outcomes.

By better addressing the external factors that have been proven to disincentivize work, mixed-income housing leads to better employment and earnings outcomes for its tenants. David Fink, the staff director of the HOMEConnecticut campaign, explains the benefits of mixed-income housing in his 2013 Tedx Talk, “Why Mixed Income Housing.” He highlights the impact of children's zip codes on their education, security, job and networking opportunities, food quality, and other community resources. Public housing developments tend to be in less affluent zip codes that are associated with crime, violence, and underfunded schools (ibid). Low-income neighborhoods also tend to have worse air pollution, which greatly contributes to the stark difference in asthma rates for low-income and high-income children (14.8 percent compared to 6.8 percent) (Rabin). Mixed-income housing allows recipients of housing assistance to relocate to better opportunity zip codes, breaking down segregational housing barriers and closing the achievement gap (ibid).

Harbor Point in Boston serves as an example of mixed-income housing's potential to transform resident outcomes. Originally named Columbia Point, the development opened in 1954 to house middle-income white families. By the mid-1960s, as public housing devolved into a last resort for poor African Americna families, Columbia Point was in a state of chaotic disrepair. Cuts to the Boston Housing Authority's (BHA) budget and a policy that no longer allowed management to enforce proper maintenance of units brought the project's decay to the point that residents interrupted a December 1969 BHA board meeting to deliver jars of cockroaches and a Christmas tree decorated with mice, all of which had been caught by the residents in their units. In addition to unsanitary conditions, Columbia Point became so unsafe that taxis, fire fighters, and ambulances refused to enter the development without police escorts.

These horrific conditions continued until 1983 when two private developers, Corcoran Mullins Jennison (CMJ) and Columbia Associates, jointly assumed ownership of the development. The developers had an ambitious goal to increase the number and quality of the units and introduce market-rate tenants to the development. Their vision was a success. When it reopened under the new name of Harbor Point in 1991, the development was a thriving mixed-income and mixed-race community. This profitable, privatized arrangement maintains the housing development to market-rate standards, allowing re-investment of revenue into community-enhancing services, such as after-school programs, goat yoga, and tuition assistance. Harbor Point was ultimately so successful that the HCV program was partly inspired by it.

A key aspect of Harbor Point's success is its partnership with Housing Opportunities Unlimited (HOU), an outsourced firm that specializes in tenant relationships. HOU representatives at Harbor Point meet regularly with tenants receiving housing assistance to quickly identify issues affecting tenant outcomes. For instance, if they see a child acting out, a HOU representative would reach out to the parent(s) to help understand the root of the problem and then work with them to provide solutions for the child. Overall, Harbor Point has become a much happier and more successful community since the implementation of mixed-income housing and now is able to provide its tenants with the necessary resources to thrive.

Conclusion

Despite public housing's deeply rooted negative stigma, housing assistance is an inarguable necessity in a nation with only 29 affordable (and suitable) market-rate rental units for every 100 extremely low-income households[11] ("The Cost of Affordable"). Still, the argument exists that public housing, in its current form, disincentivizes working. The income effect implies that housing assistance inherently increases a household's disposable income by decreasing their rent expense, therefore allowing public housing tenants to maintain or even increase their standard of living while working less. Similarly, the substitution effect implies that the Total Tenant Payment (TTP)'s marginal tax on earnings lowers the return-per-hour worked, which disincentivizes working. Additionally, Painter (2001) and Jaramillo, Rohe, and Webb (2020)

[11] Extremely low-income households, again, are defined as making 30 percent or less of the AMI.

highlighted public housing's role in a larger welfare trap, while Howard Husock (2019) details the New York City Housing Authority's dependency trap, in which almost half of its residents have received housing assistance for over 20 years. Finally, Castells (2020) summarizes existing literature that finds tenants decrease their labor force participation upon receiving housing assistance.

Yet, strong evidence also exists that public housing tenants face personal and structural barriers to employment, such as lack of childcare and transportation. Riccio et al. (2017) find that more than half of respondents faced an employment barrier, with the two most prevalent being health concerns and childcare. Jaramillo, Rohe, and Webb (2020) reaffirm these findings, concluding that employment barriers are a key determinant of labor force participation for public housing tenants. Based on this evidence, HUD could best serve its tenants by prioritizing programs that address the most common of these employment barriers. For instance, public housing developments could provide free childcare for working parents, and their management could work with local governments to facilitate nearby, reliable public transportation. PHAs could also partner with organizations like Housing Opportunities Unlimited (HOU) to address tenant needs. At the very least, however, HUD should provide its tenants with livable units in safe neighborhoods, which is unfortunately far from the current reality. Thus, HUD's recent efforts to ameliorate public housing give hope that PHAs will use successful mixed-income developments like Columbia Point as inspiration for improving tenant outcomes.

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An Analysis of Car Crashes in Massachusetts 2022

Logit, Ordered Logit, LPM, and Variable Selection

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1 Overview

1.1 Introduction

The number of fatalities from motor vehicle accidents in Massachusetts has been on the rise over the past two years. In 2022, there were 430 deaths resulting from such accidents, surpassing the earlier record of 408 fatalities in 2021.[1] Moreover, there has been a 16% increase in fatal car crashes from 2018 to 2022.[2] Given these trends, it is likely that the frequency of motor vehicle accidents will increase in the near future.

1.2 Research Question

This paper aims to identify the factors that lead to motor vehicle accidents in Massachusetts and to examine if there is a discernible relationship between the features of car crashes and the resulting injuries. While we cannot establish causation, we will attempt to isolate factors that influence the likelihoods of motor vehicle occupants dying or getting injured in a motor vehicle crash. The specific questions we seek to answer are:

What factors influence the probability of a fatal car crash?

What factors influence the probability a driver involved in a crash will experience an injury? [If a driver experiences a crash], What factors influence the probability of the severity of the driver's injury?

2 Data

2.1 Data set

Data was obtained from the Massachusetts Department of Transportation.[3] The data set contains 132,595 observations. Due to the inconsistent language used in the reported records, 54,108 records were removed to successfully run our models. After cleaning the data by removing entries without injuries reported, 78,487 observations remained. These observations yield an average of 363 crashes per day (215 crashes per day used in the study). Due to this large sample size, we believe we have substantial data to establish meaningful conclusions.

2.2 Dependent Variables

Our analysis primarily seeks to establish relationships between injuries sustained from car crashes and driving conditions. The two variables used to measure these relationships are injury and injury severity.

2.2.1 injury

The variable ”injury” is a dummy variable and records whether an injury occurred due to the impact of a motor vehicle crash. When involving two or more vehicles, both parties are considered. This variable is used in the logit, linear probability models, and variable selection algorithms.

2.2.2 injury severity

The variable injury severity is a 0, 1, 2 categorical variable and records the severity of an injury that occurred due to the impact of a motor vehicle crash. 0 signifies a minor injury and was created by merging terms such as ”Non-fatal injury - Non-incapacitating” and ”Suspected Minor Injury (B).” 1 signifies a minor injury, and was created by merging terms such as ”Non-fatal injury - Incapacitating” and ”Suspected Serious Injury (A).” 2 signifies a fatal injury occurred. This variable is used in the ordered logit model.

2.3 Quantile RHS variables

2.3.1 *speedlimit1 speedlimit2 speedlimit3*

To describe the speed limit on the roads where the crash occurred, three different thresholds were created. The boundaries were defined accordingly: *speedlimit1* refers to any speed limit below 30 MPH, *speedlimit2* refers to a speed limit from 30 MPH to 59 MPH, and *speedlimit3* refers to a speed limit above 60 MPH.

2.3.2 *age1 age2 age3*

To account for age, *age1, age2, and age3* were created to describe the combined age of both drivers (when applicable). Three different thresholds were created. The boundaries were defined accordingly: age1 if the combined driver age was below 26, age2 if the combined driver age was between 26 and 59, and age3 if the combined driver age was 60 or above.

2.4 Other Dummy RHS

We included a host of other dummy explanatory factors that may influence the injury sever-ity and injury rate of car crashes. These variables were all coded in strings, many of which contained 20 or more unique values. Our solution was a categorical simplification; assigning categories for each unique outcome based on our own judgements, and continuing with dummy variables for each outcome. For example, traffic signs held the values ”Flashing traffic control signal”, ”school zone signs”, ”stop signs”, ”traffic control signals”, ”warning signs”, ”yield signs”, etc... We decided to simplify this to 3 different values; all traffic signs, all traffic signals (signs including flashing lights or other indicators), and areas without a sign or signal. We used a similar process for the following variables:

Weather effects (baseline: *clear, cloudy, rainy, snowy*)

Whether either driver (when applicable) was distracted (looking at something away from the road, looking at an electronic device)

The type of city where the crash occurred (baseline: *rural, large urban, small urban*)

The type of terrain where the crash occurred (baseline: *level, mountainous, rolling)*

The lighting of the crash (baseline: *daylight, dusk/dawn, dark with unlighted street lights, dark with lighted street lights*)

The type of junction where the crash occurred (baseline: *one way road, twoway road, junction, driveway, highway/on ramp, railway crossing*)

The first event of the collision (baseline: *collision with object, collision with animal, collision with parked car, collision with vehicle in traffic, collision with pedestrian, collision with cyclist, collision with railway vehicle, overturned car/rollover*)

The angle of the collision (baseline: *single vehicle crash, head on crash, front to front crash, rear end crash, rear to rear crash, sideswipe same direction, sideswipe opposite direction*)

The road condition where the crash occurred (baseline*: dry, wet, gravel, icy*)

The time when the crash occurred (baseline: *afternoon* (10am-3pm), *night* (7pm-6am), *rushhour1* (6am-10am), *rushhour2* (3pm-7pm))

Whether the crash occurred in a work zone.

What type (if any) of traffic control signs were used (baseline: *no sign* (no traffic control), *traffic sign, traffic signal*)

Whether the crash involved a hit and run

2.5 Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
fatal	78,487	0.00217	0.0465	0	1
non fatal injury	78,487	0.237	0.426	0	1
no injury	78,487	0.760	0.427	0	1
distracted	78,487	0.0919	0.289	0	1
large urban	78,487	0.904	0.295	0	1
rural	78,487	0.0210	0.143	0	1
small urban	78,487	0.0755	0.264	0	1
level terrain	78,487	0.940	0.238	0	1
mountainous terrain	78,487	0.000204	0.0143	0	1
rolling terrain	78,487	0.0555	0.229	0	1
angle crash	78,487	0.245	0.430	0	1
front front crash	78,487	0.0152	0.122	0	1
front rear crash	78,487	0.0340	0.181	0	1
head on crash	78,487	0.0236	0.152	0	1
rear side crash	78,487	0.00875	0.0931	0	1
rear end crash	78,487	0.317	0.465	0	1
sideswipe od crash	78,487	0.0279	0.165	0	1
sideswipe sd crash	78,487	0.126	0.332	0	1
single vehicle crash	78,487	0.187	0.390	0	1
daylight	78,487	0.703	0.457	0	1
duskDawn	78,487	0.0434	0.204	0	1
dark lighted road	78,487	0.190	0.392	0	1
dark unlighted road_	78,487	0.0580	0.234	0	1
snow	78,487	0.0359	0.186	0	1
clear	78,487	0.675	0.468	0	1
rain	78,487	0.0752	0.264	0	1
cloudy	78,487	0.0997	0.300	0	1
fatal injury	78,487	0.00217	0.0465	0	1
injury	78,487	0.240	0.427	0	1
road dry	78,487	0.801	0.399	0	1
road icy	78,487	0.0534	0.225	0	1
road sedi	78,487	0.000968	0.0311	0	1
road wet	78,487	0.144	0.351	0	1
road st	78,487	0.0943	0.292	0	1
road oth	78,487	0.00535	0.0730	0	1
coll obj	78,487	0.132	0.339	0	1
coll animal	78,487	0.0403	0.197	0	1
coll parked	78,487	0.0542	0.226	0	1
coll vehicle	78,487	0.753	0.431	0	1
coll pedestrian	78,487	0.0100	0.0995	0	1
coll rail	78,487	7.64e-05	0.00874	0	1
coll bike	78,487	0.00663	0.0811	0	1
workzone	78,487	0.0151	0.122	0	1
junct	78,487	0.371	0.483	0	1
junct dr	78,487	0.0202	0.141	0	1
junct high	78,487	0.0428	0.202	0	1
junct rail	78,487	0.000522	0.0228	0	1
no junct	78,487	0.565	0.496	0	1
no sign	78,487	0.665	0.472	0	1
rail sign	78,487	0.000599	0.0245	0	1
sign	78,487	0.148	0.355	0	1
signal	78,487	0.187	0.390	0	1
hitrun	78,487	0.0496	0.217	0	1
speedlimit1	78,487	0.111	0.314	0	1
speedlimit2	78,487	0.649	0.477	0	1
speedlimit3	78,487	0.241	0.427	0	1
rushhour1	78,487	0.178	0.383	0	1
rushhour2	78,487	0.314	0.464	0	1
afternoon	78,487	0.298	0.457	0	1
night	78,487	0.210	0.407	0	1
age1	78,487	0.113	0.317	0	1
age2	78,487	0.701	0.458	0	1
age3	78,487	0.186	0.389	0	1
injury severity	12,466	0.156	0.399	0	2

3 Regression Analysis

To establish more convincing results, 3 different regressions and 2 different variable selection algorithms were used in the analysis. We present the findings of each regression along with our analysis.

3.1 Linear Probability Model

Linear Probability Model Regression	(1)	(2)	(3)
	injury		
VARIABLES	coef	se	pval
injury			
distracted	0.0447	0.00516	0
age2	0.00363	0.00470	0.439
age3	0.00399	0.00552	0.470
small urban	-0.0524	0.0116	6.55e-06
large urban	-0.0356	0.0105	0.000680
mountainous terrain	-0.0418	0.103	0.684
rolling terrain	0.00293	0.00643	0.648
angle crash	0.0434	0.00812	8.70e-08
front rear crash	-0.0309	0.0110	0.00481
head on crash	0.292	0.0117	0
rear side crash	-0.129	0.0174	0
rear end crash	-0.000228	0.00801	0.977
rear rear crash	-0.128	0.0219	4.99e-09
sideswipe od crash	-0.0219	0.0115	0.0571
sideswipe sd crash	-0.107	0.00851	0
front front crash	0.106	0.0141	0
duskDawn	-0.00555	0.00757	0.464
dark lighted road	-0.00141	0.00547	0.797
dark unlighted road	0.000957	0.00783	0.903
snow	-0.0304	0.0109	0.00551
rain	-0.0119	0.00775	0.125
cloudy	0.00302	0.00502	0.547
road wet	-0.00914	0.00585	0.119
road icy	-0.0755	0.00926	0
road sedi	0.0242	0.0471	0.607
road st	-0.0196	0.00518	0.000150
road oth	-0.0186	0.0201	0.355
coll animal	-0.239	0.00864	0
coll parked	-0.0822	0.0101	0
coll vehicle	0.000754	0.00821	0.927
coll pedestrian	0.546	0.0153	0
coll over	0.355	0.0260	0
coll rail	0.187	0.175	0.284
coll bike	0.479	0.0192	0
workzone	-0.0251	0.0121	0.0370
junct	0.000170	0.00438	0.969
junct dr	-0.0646	0.0106	1.15e-09
junct high	-0.00991	0.00773	0.200
junct rail	-0.125	0.0730	0.0877
sign	-0.0144	0.00523	0.00588
signal	0.00467	0.00489	0.339
rail sign	-0.0145	0.0679	0.831
hitrun	-0.104	0.00688	0
speedlimit2	0.0395	0.00482	0
speedlimit3	0.0408	0.00548	0
rushhour1	-0.00129	0.00444	0.772
rushhour2	-0.000496	0.00397	0.900
night	0.0562	0.00617	0
Constant	0.241	0.0128	0
Observations	78,487		
R-squared	0.078		

3.1.1 Results

The LPM model serves as a baseline for us to get a sense of the relationships between injury and our RHS variables. The results indicate that distracted, crash angle, initial collision types, and hit and runs are the most incrementally significant variables in predicting injury. Distracted drivers are 5% more likely to get into accidents that cause injury, and head-on/front-to-front crashes are the most dangerous at 20% and 10% higher likelihoods of injury relative to single vehicle crashes. Our highest coefficients by far are for initial vehicle collisions with bikers and pedestrians, but this is self explanatory as pedestrians and bikers have no protection against moving vehicles.

3.2 Logit Model

Logit Regression	(1)	(2)	(3)
	injury		
VARIABLES	odds ratio	seEform	pval
injury			
distracted	1.272	0.0364	0
age2	1.022	0.0287	0.430
age3	1.024	0.0337	0.471
small urban	0.715	0.0509	2.48e-06
large urban	0.792	0.0507	0.000266
mountainous terrain	0.717	0.542	0.660
rolling terrain	1.019	0.0388	0.623
angle crash	1.320	0.0635	7.84e-09
front rear crash	0.875	0.0584	0.0451
head on crash	4.009	0.256	0
rear side crash	0.351	0.0509	0
rear end crash	1.043	0.0497	0.378
rear rear crash	0.310	0.0636	1.12e-08
sideswipe od crash	0.920	0.0641	0.231
sideswipe sd crash	0.478	0.0259	0
front front crash	1.788	0.137	0
duskDawn	0.958	0.0441	0.350
dark lighted road	0.982	0.0323	0.588
dark unlighted road	1.008	0.0483	0.860
snow	0.804	0.0572	0.00223
rain	0.931	0.0428	0.120
cloudy	1.018	0.0302	0.553
road wet	0.951	0.0330	0.147
road icy	0.627	0.0370	0
road sedi	1.148	0.304	0.602
road st	0.883	0.0279	7.82e-05
road oth	0.885	0.111	0.330
coll animal	0.103	0.00978	0
coll parked	0.515	0.0344	0
coll vehicle	0.984	0.0477	0.739
coll pedestrian	12.97	1.231	0
coll over	4.767	0.631	0
coll rail	3.055	2.917	0.242
coll bike	8.877	0.975	0
workzone	0.855	0.0636	0.0352
junct	0.995	0.0255	0.838
junct dr	0.658	0.0456	1.51e-09
junct high	0.940	0.0432	0.181
junct rail	0.378	0.212	0.0826
sign	0.923	0.0281	0.00878
signal	1.023	0.0289	0.430
rail sign	0.958	0.409	0.920
hitrun	0.458	0.0238	0
speedlimit2	1.273	0.0379	0
speedlimit3	1.286	0.0434	0
rushhour1	0.988	0.0263	0.662
rushhour2	0.995	0.0234	0.830
night	1.404	0.0517	0
Constant	0.315	0.0245	0
Observations	78,487		

LPM vs. Logit GOF		
r2	0.0776	
pseudo r2		0.0710
ll	-41382.2	-40151.0
aic	82862.5	80400.0
bic	83316.7	80854.3

3.2.1 Results

Comparing the LPM and Logit models, we believe the Logit model is a better model. It features a slightly lower pseudo R2 than the linear model, but has a higher Log Likelihood and lower AIC and BIC statistics. Due to these statistics, we believe the Logit model strikes a better balance between fit and complexity. Our following analysis is made using the output of the Logit regression model.

We are surprised to see several coefficients that indicate negative relationships with injury that go against our intuition. Bad weather and icy/wet roads result in lower probabilities of injury even though driving conditions are more hazardous. Urban areas see lower probabilities of injury as well, but this may make sense as speed limits are lower and roads are often more congested. Despite the vast majority (76,841 out of 78,487 observations) of analyzed accidents occurring in urban areas, there is a lower chance of serious injury for accidents in urban areas compared to rural areas. Generally, any crash angle that is not head-on or front-to-front results in lower probability of injury compared to crashes without multiple vehicles, with the exception of angle crashes, which increase the odds of injury by 32%.

One variable we were very interested in was junction type, comparing injury probabilities across one or two way roads with areas like T or Y intersections and highways and ramps. The results indicate that there is no significant difference in injury probability between regular roadways and intersections or junctions, so there is no added risk of injury in dense traffic areas compared to open stretches of roadways. Our only significant dummy is driveways where there is much less chance of injury.

Our research also looked into the influence of age and speed limits on accident outcomes.

The propensity for older drivers to be involved in accidents with injuries was ambiguous; on one hand, they may have delayed reactions yet on the other, they benefit from greater driving experience. In contrast, younger drivers might be more prone to risky behaviors due to impulsiveness. Our findings through age quantile analysis revealed no notable disparity in accident-related injuries across different age cohorts. On the subject of speed limits, our analysis yielded more definitive results. It was observed that on roads where speed limits range between 30-59 mph and exceed 60 mph, there is a similar, approximately 28% heightened likelihood of accidents resulting in injuries.

One of the more surprising results is the insignificance of our variables devoted to time. *Night* was significant compared to *afternoon* with a 41% increase in the odds of injury, but our dummies for rush hour times were insignificant with coefficients close to 0. We suspected that driving in rush hour would lead to more dangerous car crashes due to the increased frequency of cars on the roads and driver fatigue, but it appears that driving at rush hour does not increase the odds of an injury compared to driving at other hours of the day. Likewise, the condition of road lighting did not show any meaningful impact on crash outcomes. Whether driving at twilight, dawn, or on roads that were either well-lit or not illuminated at all, there was no noticeable variance in the likelihood of sustaining injuries from accidents.

With regards to traffic controls, our results are mixed. Since our dependent variable is injuries resulting from accidents, we cannot make any conclusions as to the efficacy of traffic signs in safe driving, but we can talk about how they may change the results of the crash. Relative to roads with no signs, traffic signs are observed to decrease the odds of injury by about 8%. However, the presence of traffic signals, which constitute traffic signs with glowing indicators, are insignificant and feature an odds ratio above 1. Intuition tells us that these traffic signals should be easier to recognize and observe than simple road signs, yet have no effect on injury probability.

Our dataset encompasses a variety of initial collision scenarios, with crashes involving stationary objects serving as the baseline in our regression models. Contrary to expectations, the data indicates that the likelihood of injury from a crash involving another moving vehicle does not significantly differ from collisions with stationary objects. We anticipated a higher odds ratio for such incidents. Furthermore, the odds ratios for accidents involving parked vehicles or animals are notably low, which aligns with the intuition that these types of collisions generally carry less risk than those involving moving vehicles or substantial structures. However, the data clearly shows that overturns and rollovers present a considerably higher risk, with the probability of injury increasing by 400% compared to collisions with stationary objects.

3.3 Ordered Logit Model

Ordered Logit Regression	(1)	(2)	(3)
VARIABLES	odds ratio	seEform	pval
injury severity			
distracted	1.082	0.0881	0.333
age2	1.080	0.0927	0.373
age3	1.017	0.103	0.869
small urban	0.870	0.173	0.484
large urban	0.977	0.170	0.891
mountainous terrain	5.761	7.795	0.196
rolling terrain	0.899	0.103	0.357
angle crash	0.816	0.0970	0.0871
front rear crash	0.541	0.115	0.00379
head on crash	1.711	0.226	4.84e-05
rear side crash	0.294	0.218	0.0987
rear end crash	0.418	0.0523	0
rear rear crash	0.341	0.356	0.303
sideswipe od crash	0.800	0.152	0.242
sideswipe sd crash	0.615	0.0924	0.00123
front front crash	0.791	0.160	0.245
duskDawn	1.173	0.152	0.218
dark lighted road	0.901	0.0875	0.282
dark unlighted road	1.016	0.137	0.907
snow	0.820	0.197	0.408
rain	0.806	0.116	0.132
cloudy	0.948	0.0853	0.550
road wet	0.999	0.106	0.995
road icy	0.749	0.148	0.144
road sedi	1.842	0.977	0.250
road st	1.227	0.108	0.0202
road oth	0.599	0.282	0.277
coll animal	0.810	0.261	0.514
coll parked	1.889	0.351	0.000623
coll vehicle	1.366	0.171	0.0124
coll pedestrian	3.619	0.436	0
coll over	1.265	0.325	0.360
coll rail	16.10	32.56	0.170
coll bike	1.796	0.323	0.00113
workzone	0.690	0.193	0.184
junct	0.873	0.0671	0.0770
junct dr	0.879	0.181	0.530
junct high	0.710	0.123	0.0476
junct rail	4.976	8.299	0.336
sign	0.869	0.0812	0.133
signal	0.880	0.0762	0.141
rail sign	1.452	2.318	0.815
hitrun	0.865	0.154	0.418
speedlimit2	1.121	0.100	0.199
speedlimit3	0.895	0.0920	0.280
rushhour1	0.955	0.0828	0.596
rushhour2	0.985	0.0723	0.840
night	1.388	0.150	0.00237
/cut1	6.368	1.389	0
/cut2	80.90	18.63	0
Observations	12,466		

3.3.1 Results

Now that we have investigated how each RHS variable affects the probability of injury, we move into an analysis of predicting injury severity with an ordered logit model.

Generally, we observe similarities with the logit model, where variables that are associated with higher probabilities of injury are also associated with a higher severity of injury in cases where an injury occurs. For example, head-on and front-to-front crashes, which predict much higher probabilities of injury, have odds ratios much higher than 1 for the different levels of injury severity. Crashes occurring at night also observe higher odds of more severe injuries.

Interestingly, some of our variables now contain much larger odds ratios for predicting injury severity. An example of this is mountainous terrain (as it compares to level terrain). In the logit model, mountainous terrain resulted in a 29% lower chance of injury, but in the ordered logit it shows a 576% increase in the odds of more serious injuries.

Unfortunately, many of the coefficients in the ordered logit results lack statistical significance, including the 576% increase in severe injury for mountainous terrain compared to level terrain. This is likely due to our lack of data; in predicting injury severity we can only compare across accidents that cause injury, for which we have only 12,466 observations. Within this group, many of the variables with large or small odds ratios are sparse; mountainous terrain crashes resulting in injury make up only 3% of these observations, which likely explains the significance attached to its odds ratio. We would like to see this analysis replicated with more data, preferably data that comes not from an individual state dealing with these specific issues.

3.4 Variable Selection Algorithms

3.4.1 Backwards Variable Selection

Backwards Stepwise Regression	(1)	(2)	(3)
	injury		
VARIABLES	coef	se	pval
injury			
junct dr	-0.420	0.0686	9.21e-10
speedlimit2	0.240	0.0297	0
distracted	0.240	0.0285	0
small urban	-0.332	0.0707	2.60e-06
large urban	-0.231	0.0634	0.000264
night	0.329	0.0214	0
workzone	-0.152	0.0742	0.0404
angle crash	0.251	0.0214	0
front rear crash	-0.164	0.0510	0.00125
head on crash	1.360	0.0499	0
rear side crash	-1.075	0.139	0
coll over	1.545	0.131	0
rear rear crash	-1.202	0.201	2.07e-09
sideswipe od crash	-0.112	0.0551	0.0424
sideswipe sd crash	-0.769	0.0341	0
front front crash	0.552	0.0634	0
coll bike	2.192	0.103	0
speedlimit3	0.245	0.0333	0
hitrun	-0.778	0.0518	0
snow	-0.231	0.0700	0.000951
rain	-0.123	0.0332	0.000210
coll animal	-2.286	0.0928	0
coll parked	-0.647	0.0498	0
road icy	-0.466	0.0573	0
sign	-0.0933	0.0250	0.000195
road st	-0.125	0.0314	7.15e-05
coll pedestrian	2.556	0.0920	0
Constant	-1.124	0.0698	0
Observations	78,487		

3.4.2 Forward Variable Selection

Forward Stepwise Regression	(1)	(2)	(3)
	injury		
VARIABLES	coef	se	pval
injury			
head on crash	1.360	0.0499	0
coll pedestrian	2.554	0.0920	0
sideswipe sd crash	-0.771	0.0341	0
coll animal	-2.288	0.0928	0
coll bike	2.190	0.103	0
coll parked	-0.648	0.0498	0
night	0.329	0.0214	0
hitrun	-0.779	0.0518	0
road icy	-0.478	0.0581	0
coll over	1.546	0.131	0
angle crash	0.250	0.0214	0
distracted	0.240	0.0285	0
front front crash	0.552	0.0634	0
rear side crash	-1.076	0.139	0
junct dr	-0.420	0.0686	8.82e-10
rear rear crash	-1.203	0.201	2.01e-09
speedlimit2	0.239	0.0297	0
speedlimit3	0.245	0.0333	0
road st	-0.124	0.0314	7.54e-05
sign	-0.0936	0.0250	0.000187
road wet	-0.0511	0.0339	0.132
front rear crash	-0.165	0.0510	0.00125
small urban	-0.333	0.0707	2.50e-06
large urban	-0.232	0.0634	0.000249
snow	-0.218	0.0708	0.00208
workzone	-0.153	0.0742	0.0392
sideswipe od crash	-0.113	0.0551	0.0407
junct rail	-0.838	0.482	0.0820
rain	-0.0775	0.0450	0.0852
Constant	-1.118	0.0699	0
Observations	78,487		

Logit vs. Backward vs. Forward GOF			
pseudo r2	0.071	0.071	0.071
ll	-40151.0	-40158.3	-40155.3
aic	80400.0.5	80376.6	80374.7
bic	80854.3	80654.7	80671.3

Due to the complexity of our model, we employ stepwise regression in an attempt to simplify our results. We used both a forward and backward selection process with a p-value probability cutoff of 0.1.

Both methods resulted in dropping variables for junction type, time, lighting, and traffic controls. As mentioned earlier, these were variables that did not result in significant coefficients for the majority of dummies included in the previous models.

Despite some metrics suggesting marginal enhancements with stepwise models over the Logit, we maintain that our initial model remains superior. The comparative analysis reveals that both models yield identical pseudo-R-squared values, yet the stepwise versions exhibit marginally inferior log likelihoods, suggesting they do not fit the data as well as the original logit. Although the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are slightly improved with reductions of .03% and .2% respectively, this comes at the cost of excluding 19 variables from our analysis. We contend that these variables, although omitted in the stepwise models, act as critical control factors in the Logit model and their inclusion outweighs the minor gains in (GOF) metrics.

The stepwise models do address the issue of multicollinearity more effectively by eliminating variables that exhibit collinearity, such as weather versus road conditions and time of day versus lighting conditions. This is a favorable adjustment from the original model. Nevertheless, these models tend to favor variables that, while statistically significant, do not contribute meaningfully to our research objectives—for instance, the correlation between pedestrian involvement and an increased probability of injury.

Considering these points, we assert that the original Logit model is the most representative and informative with respect to our research aims, and thus we consider it to be the optimal choice.

4 Conclusions

As previously noted, more than 400 people living in MA lost their lives due to motor vehicle crashes in 2022. The data set used in this analysis found that over 19,000 people sustained some form of reported injury, although that number is likely higher due to inaccurate reporting. Of those involved in car crashes, 21%-67% of motorcycle crash survivors experience depressive mood and up to 47% experience elevated anxiety and driving phobia[3].

Seemingly contradictory conclusions include crashes occurring with snow and/or on icy roads decrease the probability of injury. However, it's important to note that drivers may slow down during these conditions, reducing the speed and risk of injury. No effects from time of crash, traffic controls, and junction type were observed, but this research likely requires different data and research process.

This is an observational study so we cannot make any conclusions about the causal effects of these variables. Ultimately, there are many factors that contribute to crash severity and possibility of injury, and many of them are outside our control. It's inconvenient to actively avoid driving on roads with slightly more dangerous conditions, but there are some recommendations we can make. If possible, avoid driving at night to reduce the probability of injury. Pedestrians and cyclists should have extreme caution around motor vehicles. And finally, and most importantly, distracted driving has real, fatal consequences that can hinder the lives of other drivers and passengers. Drive safe, and stay alert on the roads!

5 Sources

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