# The Toll of Commuting: The Effects of Commute Time on Well-Being M. Thomas Marshall, Jr. Kent P. Kimbrough, Faculty Advisor Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University.

Duke University
Durham, North Carolina
2018

# Acknowledgements

I would like to thank my thesis advisor and seminar professor, Kent Kimbrough, for his guidance throughout the development of this paper. His feedback, advice, and support made this work possible. I'd also like to thank Professors Charles Becker, Patrick Bayer, and Thomas Nechyba for sharing their insights and expertise, and their willingness to answer my frequent questions. Lastly, I would like to thank my Honors Thesis Workshop classmates and my good friend Max Stayman for their comments and ideas throughout the research and writing process.

Abstract

When deciding on housing location, people theoretically optimize for the best location given

their commute time, housing cost, income, as well as other factors. Stutzer and Frey (2008)

suggest that this is not true in some nations, such as in their investigation of Germany, with their

results showing that the cost of an average commute is equivalent to 35.4% of the average

income. This paper investigates the impact of commute time on the well-being of individuals in

the United States, correcting for various other factors that determine housing choice such as race,

age, and whether they have a child living at home. The results of this study are clearly that the

relationship found between commuting time and well-being cannot be proven to be statistically

significant from zero, so there is not any evidence against optimization.

JEL Classification: D12; D61; R31; R41

Keywords: Commuting; subjective well-being; location theory; housing choice; monocentric city

model

3

### I. INTRODUCTION

Commuting is a big part of many Americans' lives and it's often one of the more unpleasant parts of the day. This is particularly true for those who live in major cities with lots of traffic. It's no secret that getting stuck in traffic jams to and from work can be very frustrating and stressful, yet people still have long commutes. People may choose to live far from their places of work for a wide variety of reasons, such as housing cost or school quality. What are the tradeoffs that people are making when deciding where to live? And are people, in particular Americans, underestimating the impact that long commutes can have on their well-being?

# The growing American commute Average travel time to work, 1980 - 2014 26 minutes WAPO.ST/WONKBLOG Source: US Census

Figure 1: Average Travel Time to Work in the United States over Time

The issue of commuting negatively impacting quality of life is especially important in the United States today. Commuting times in the US are the highest they have been since the US Census has been collecting data on them, with the average commute time up to 26 minutes in 2014 (Christopher Ingraham, 2016). These times were below 22 minutes in 1980, (Figure 1) but climbed quickly until 2000. Since 2000, growth in commute times has slowed, but seems to be

continuing the upward trend. If commute times continue to rise, will people be less happy? If so, there is a possibility that there could be a bigger depression incidence.

There are also a large number of costs associated with commute time. First, there are the direct costs of commuting such as individual costs on transport and gas, as well as public costs such as pollution and infrastructure degradation. Travel times also present an opportunity cost for the commuter; as the time increases so does the cost. While commuting times will never drop to zero, a growing average commute time is a greater detriment on the United States economy because it takes additional time that people could otherwise be productive.

In addition to rising commuting times, there is also an increase in what are known as "super-commuters." There are various definitions for super-commuters, such as "a person who works in the central county of a given metropolitan area, but lives beyond the boundaries of that metropolitan area," or commute with times over one hour or over 90 minutes (Moss and Qing, 2012). Either way, Moss and Qing (2012) showed that the number of super-commuters, particularly in the largest US metropolitan areas, has been increasing in recent years. As the number of super-commuters continues to grow, how will this impact our urban spaces and the experiences of these individuals with extended commutes?

This paper will primarily investigate the impact of commuting on well-being. One could assume that people optimize housing choices to reduce cost and commute while increasing school quality and many other factors. In that case, the marginal change in well-being for additional commuting time should be nearly zero because people balance the various tradeoffs in housing location in order to optimize to their situation. However, it is also possible that people frequently fail to optimize on housing choice, whether it be from irrationality or structural

societal issues. This paper will attempt to investigate different determinants of housing choice in order to see how they affect people's commuting patterns and overall well-being.

First I will review some relevant literature, including the paper whose methods I will partially replicate for the United States. I will then discuss the methodology that I will use to further investigate this question. After that I will discuss my data and the benefits and issues that come with it. Next, I will discuss my Empirical Specifications and the results that I get from my regressions, before finishing with a conclusion that further analyzes the results. The results of this study are that there is no significant relationship between commute time and well-being, giving no evidence that people are failing to optimize their housing choices.

### II. RELEVENT LITERATURE

The main paper that I have used as my inspiration is a paper by Stutzer and Frey (2008) titled, "Stress that Doesn't Pay: The Commuting Paradox." In this paper, Stutzer and Frey used data from the German Socio-economic Panel Study (GSOEP) to test the effects of commuting on subjective well-being. The GSOEP had questions on demographic data, income, housing costs, as well as daily one-way commute time. In addition, it had a question which asked survey participants, "How satisfied are you with your life, all things considered?" which they would answer on a scale of 0 to 10.

To test the effect of commuting time on this life satisfaction, which Stutzer and Frey call subjective well-being, they made the assumption that well-being is a function of commute time, income, and rent. In theory, everyone should live in a location that optimizes their well-being based on these three variables.

Based on this assumption that everyone optimizes their location, at the margins a change in commute time should have no impact on well-being. In theory, people make tradeoffs between the three variables in the function - commuting time, income, and housing costs - so they might choose to live further away from their place of work in order to spending less on housing, or they might live closer to work at the expense of higher housing costs. When people are choosing the locations of where they live they should be looking for this perfect equilibrium, where they balance all the different factors of housing choice that will impact their lives as best they can. Because of this optimization, they should not be fundamentally biased against one determinant of housing choice because in theory everyone is balancing their own choice and finds the housing that is best suited to their needs and thus maximizes their well-being.

Using this theoretical framework, Stutzer and Frey were able to set up a regression that accounts for the three variables within the function for well-being as independent variables and uses well-being as the dependent variables. They also used a variety of demographic variables in order to remove any bias that those would have on the results. They used a pooled least-squares regression because they used data from across multiple years, but this will not apply to my paper because I will only be using longitudinal data from one point in time.

Their regression showed that people with a longer time spent commuting had worse well-being, when taking into account these different variables that were in their function for well-being. The effect on well-being by commute time was decently large and statistically significant. On average, one additional hour commuting led to a decrease of 0.28 in well-being (on a 10 point scale). The average well-being score was 7.13. As Figure 2 below shows, the range of well-being was moderate, so this decrease of 0.28 is greater than the difference between the first quartile and the fourth quartile. An additional hour of commute time was therefore greater than

the range of the quartiles. Another important result is that the fourth quartile is much further away from the other three, showing that those with the longest commute times experience the most negative impact on life satisfaction.

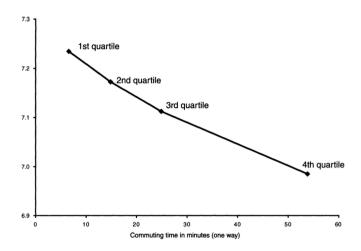


Figure 2: Commuting time and average reported satisfaction with life, Germany 1985-2003 (GSEOP), Stutzer and Frey, (2008)

In addition to that main test, Stutzer and Frey (2008) performed a variety of other tests on their data set. For example, they look at the effect of mode of transportation on their results from above. One of their more interesting other studies explored how much more an individual would need to be paid in order to be as well off as someone who doesn't commute at all. Their results showed that for someone with the average commute in Germany of 22 minutes each way to be just as satisfied as someone who does not commute, all else being equal, a person would need 470 euros per month, which is 35.4% of the average monthly labor income. 35.4% of the average income is a large amount, showing the high cost that people in Germany are failing to account for in their housing choice.

They continue to look for solutions to what they call the "commuting paradox," that people are less satisfied with life when they have longer commutes, despite the initial theory that they should adjust accordingly with the other variables in the function for well-being. First, they

test on a household level by including one's partner's commute time as well. They find that there is little to no evidence that a partner's commute explains the failure to optimize. In addition, they look at other causes of satisfactions as well as frictions from people being resistant to moving.

These are all additional investigations that I can look into to further investigate this topic.

For my paper, I hope to replicate much of the methodology of the Stutzer and Frey (2008) paper, and apply it to the United States. The main goal will be to determine whether this "commuting paradox" exists in the United States, and if so, how its scale compares to the one in Germany. The development patterns and spatial layouts of Germany and the United States are very different, so it will be interesting to see if that has an effect on the commuting paradox. Additionally, this should reveal some of the tradeoffs that people are making at the margins when deciding on where to locate their homes or apartments, which will provide additional insights as well.

There are numerous additional papers in urban economics that relate to the study of commute time and welfare. Some in particular that are important to this investigation are those discussing the validity of the monocentric city model. The model predicts that "residential density and rent gradients will be both downward sloping from the central business district (CBD) and convex," as described by Hamilton and Röell (1035). As Hamilton and Röell continue to discuss in their paper "Wasteful Commuting," this theory of rent gradients downward sloping as you stray further from the central business district has failed in multiple ways. First, the gradient is not always downward sloping, as it is often zero or positive, meaning that rent prices increase at certain points as you go further away from the city center. The second issue is that it often cannot be considered a "gradient" at all, given stark divides in neighborhoods and housing stock, which is the overall supply and nature of residential space in a city, often caused

by suburban sprawl. These issues challenge the validity of the monocentric city model, which questions the ability of individuals to have available marginal choices of housing stock, allowing the market to truly dictate commute times. If there are fundamental issues in the layout of American cities that don't allow for people to have adequate housing options, then housing choice and commute time cannot be optimized.

White (1988) criticizes Hamilton and Nöell's rejection of the monocentric city model, criticizing their methodology and claiming that they oversimplified the issue at hand. While that may be true, she also agrees that the monocentric model has major flaws, such as discrepancies in housing stock, as well as a failure to account for the limitations that road structures place on commuting patterns. Despite her critique, she furthers the idea that there are externalities in play that prevent commute time from truly optimizing. These externalities, mainly structural issues determined by the layout and geography of our cities, would be difficult to account for but are a major factor in housing choice.

One additional paper that discusses the theory of housing choice is "The Effects of Housing Prices, Wages, and Commuting Time on Joint Residential and Job Location Choices" by Kim S. So, Peter F. Orazem, and Daniel M. Otto. This paper discusses the differences in decisions of living and working in rural and urban areas. It utilizes housing prices, wages, and commute times as the main determinants of housing location choice, similar to the Stutzer and Frey piece. While its results aren't particularly relevant to this paper, its underlying theory is. One of the useful points that it makes is that wages and housing prices don't necessarily need to be adjusted for cost of living to understand housing choice. Housing cost and wages have a high correlation with costs of living associated with more urban areas, so these two will balance out differences in affordability and cost of living.

# III. THEORETICAL FRAMEWORK

To understand the effects that commute time have on well-being, I have attempted to isolate commute time as a factor of well-being by whatever methods possible. Obviously there are countless factors in overall well-being, so this is a challenge. Stutzer and Frey argue that income and housing costs are important variables because they have major explanatory power in both commute time and well-being. Housing costs are very important in theory because they are a major factor in where people live, as people often live further away from their place of work to save money on housing costs. The reality, particularly in the United States with its sprawling suburbs, may not follow the theory that housing costs and distance from work have an inverse relationship.

For their main investigation, Stutzer and Frey used income, housing cost, and commute time as their three independent variables that served as a function of well-being. As I began by trying to recreate their experiment for a new location and situation, my first test was replicating their methods. Using these three independent variables and a proxy for well-being, I performed a least-squares regression in order to find the basic effects of commute time on well-being in the United States. These variables provide explanatory power in regard to the tradeoffs that individuals make when deciding between housing locations, namely how much money they make, the cost of the housing, and the time spent commuting to work.

$$Y_i = \beta_1 Commute_i + \beta_2 Income_i + \beta_3 HousingCost_i + \varepsilon_i$$
 (1)

These three core independent variables will make up the base of my model, as their explanatory power is proven by Stutzer and Frey's investigation (Equation 1). However, I was not completely convinced that those three independent variables were the only variables that should be used to determine housing choice and well-being. I tested a variety of other variables

to further investigate this relationship, including whether the individual's home was located in a central city or in a Metropolitan Statistical Area, their age and race, and whether or not they had a child living at home with them. All of these variables are major determinants of housing location choice, so I think we can assume that people are balancing out these different factors when deciding where they will live. City residents would be hypothesized to behave differently than those in their city's suburbs and even more differently than those who live in rural areas; as there is evidence that the economic decision-making methods of each of those three groups are different (Lundberg, Komarovsky, & McInerny, 43). Age is likely a factor because older people are less likely to move. Ongoing (albeit unofficial) segregation in American cities also makes race a major factor in determining where people can live. Lastly, having a child at home makes it more likely that they are choosing their home location based on the child's school in addition to the individual's workplace.

Similar to the theory behind the Stutzer and Frey piece, at the margins people's overall well-being will not change based on small tradeoffs between commute time. I also ran the same regressions modifying the commuting, income, and housing costs variables in order to give each of them a slightly more normal distribution. Adding these various models of housing location choice to the experiment will add further aspects of depth to this investigation, as it should provide explanatory power to why people live in certain locations, particularly those that are far from their workplace.

### IV. DATA

The data used in this study comes from the National Longitudinal Survey of Youth 1979, which gives individual-level data from the same people across the United States on a wide

variety of topics. For my research investigations, I will limit the data to a single year in order to ensure consistency of survey questions and data necessary to investigate these relationships.

Therefore the reasoning for getting a longitudinal study was not to compare the effects on people over time, but to acquire data on a wide variety of topics from single individuals, in an attempt to understand certain causes of their well-being.

The data from NLSY79 is free and accessible online, which makes it fairly easy for me to work with. There are thousands of variables available, as there are more than twenty iterations of the survey, each with hundreds of variables. However, despite the overwhelming amount of variables available, the online data investigator makes it fairly easy to find the different options available and add it to an exportable data file. It easily exports in a variety of file types including .csv files, which are easy to export to Stata. There are a few things that must be done to clean up the data, such as to rename each variable from its identification number to an actual name and to remove the values of fields that were left blank, represented by a -4, or when people didn't participate in the survey that year, as indicated by a -5. Of course, this data cleaning is very easy to do in Stata and does not take up a significant amount of time.

As I mentioned before, the three independent variables that I needed in order to replicate the main investigation of the Stutzer and Frey piece are commute time, income, and housing cost, with a measure of life satisfaction as the dependent variable. I will now go through each of these and describe what the NLSY79 includes for these variables. I also needed other variables as well such as age, race, and whether they have a child living at home, which are all also included in this data set. It contains data on a fairly wide variety of individual characteristics, so I am not concerned about the availability of those data sources, as it appears to have all of the topics I will need data from.

The first of those key data sets that I will need is commute time. The NLSY79 has great data on this in the years that it asks this question, but unfortunately those years are limited. The years this has been asked are 1979, 1980, 1981, 1988, 1993, and 1994. However, 1994 is the only year that has data for both of the most important variables – commute time and a proxy for well-being. Therefore I must use solely the 1994 data in order to see the effects of current commute time on present well-being. The commuting data in the 1994 sample is thorough and easy to use. The data source has additional data on when people have multiple jobs, all the way up to five. While the effects of multiple jobs on the relationship between well-being and housing choice has not yet been investigated, it is definitely an interesting topic for further study and expansion in the future.

**Table 1** Summary of Main Variables

Variable	Observations	Mean	Std. Dev.	Min.	Max.
CES-D Score (Proxy	8,875	17.22975	4.079757	0	21
for Well-Being)					
Average Daily	7,324	21.09134	18.62535	0	240
Commute Time, One-					
Way					
Total Individual Annual	8,472	19,533.68	18,941.99	0	101653
Income					
Market Value of	4,043	101,363.9	80,706.53	0	470,417
Residential Property					
Owned					
Age	8,889	32.97716	2.239094	29	37
Central City Dummy	8,413	.1507191	.3577962	0	1
MSA Dummy	8,413	.8120765	.3906743	0	1
Black Dummy	12,686	.2501971	.4331435	0	1
Hispanic Dummy	12,686	.1578118	.3645788	0	1
Child at Home Dummy	8,729	.5573376	.49673	0	1
Normalized Commute	7,324	1	.8830805	0	11.37908
Time					
Natural Log of Income	6,854	9.736157	1.037685	1.791759	11.52932
Natural Log of Housing	4,040	11.21374	.9000435	4.094345	13.06137
Cost					

The variable for commute time has 7,324 data points, which is smaller than the whole NLSY79 survey, because it only takes into account people with jobs, who filled out the survey in 1994, and didn't leave the question blank. This means that the true full sample size of people who took the survey in 1994 is around the 8,875 people in the CES-D variable. The minimum commute time is 0 minutes, and after removing a few extreme outliers, which were assumed to be data input errors as they were all above an eight hour commute each direction, the maximum is 240 minutes. This is a four-hour commute each direction, so there are still some very long commutes in the sample. The mean commute time of the data set is 21.09 minutes, which slightly lower than the average US commute time in the 1990 US Census, which was 22.4 minutes. Because later US Census data has shown that commuting data has continued to grow post-1990, the NLSY79 1994 sample's commute time mean is likely a little less than the nation as a whole, but not too far off actual value.

The next variable is income. This one is fairly simple; I will take the data from the NLSY79 data from 1994 for "Total Income from Wages and Salary in Past Calendar Year." This is probably the easiest variable to understand, and the maximum seems to be reasonable values. The minimum value for income is 0, and the maximum is \$101,653. The mean value is \$19,533, which may sound low but is not as low as it seems. In addition to inflation since 1994, this is just income of an individual, not a total household. The median income is \$16,937.50. The main reason that the sample has small mean and median income is that this sample contains only younger people, so they are at earlier stages in their careers where they likely are paid less than their older counterparts. The ages in this sample range from only 29 through 37. A greater diversity in ages might create better results, but that is not possible with the nature of this survey. While the U.S. Census does not publish results for every age's income every year, they do have

ranges of ages that are applicable here. In 1994, the age group of 24 years old to 34 years old, which is pretty representative of our sample, individuals had a median income of \$18,815, and a mean income of \$22,296 (U.S. Census Bureau, "Historical Income Tables"). Those are both slightly higher than the mean and median incomes of our sample, but give me confidence that the data in this sample are roughly in line with national levels.

The last of the original independent variables used by Stutzer & Frey is housing cost. This unfortunately is the biggest limitation of the NLSY79 data set, because there is no variable for "total housing cost." Instead, the best option available is to utilize the data for "Market Value of Residential Property Owned." The clear problem in this situation is that it limits the research to those who own homes as opposed to all members of society. It ignores those who rent or live with someone else such as a family member. It also ignores the fact that most people have debt on the properties they own, such as mortgages. Limiting our data to homeowners will also lead to complications around stickiness, given that owners are five times less likely to move than renters (Ihrke, Faber, & Koerber, 2011). They achieved this result even when controlling for all other variables such as age, since renters are on average younger than homeowners, and younger people have higher rates of geographic mobility. The mean for this data set is \$101,363 for market value, and the median is \$80,000. This is lower than the median market value of homes in the United States in 1994, which was \$101,100. One other note with this particular data set is that the question is phrased "About how much do you think this property would sell for on today's market?" This simplifies the issue, getting rid of problems with tax assessors or time since last sale, but it does leave the valuation of the house in the hands of people who are not experts and also may have bias in what they think their home is worth, even if this survey's results have no impact on their ability to sell their home.

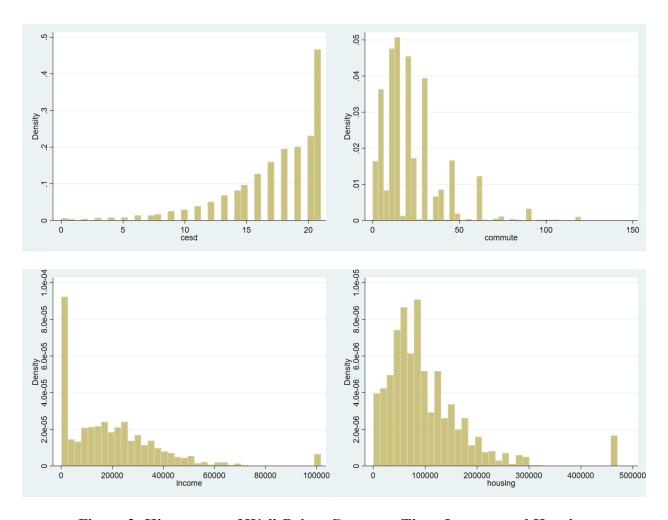


Figure 3: Histograms of Well-Being, Commute Time, Income, and Housing

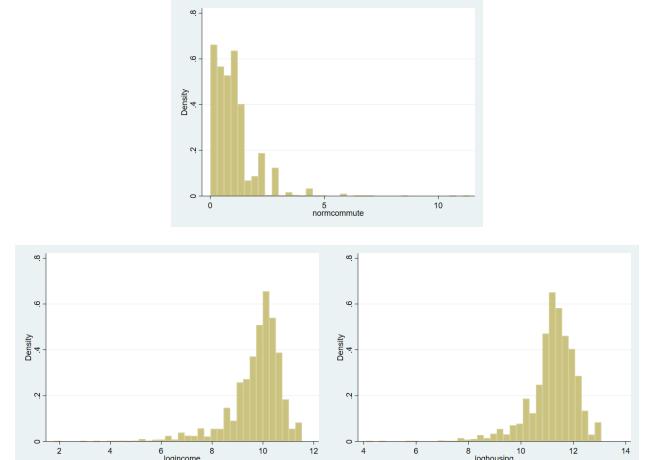


Figure 4: Histograms for Normalized Commute Time, Natural Log of Income, and Natural Log of Housing Cost

An issue present with these three core independent variables is that none of them followed a very normal distribution, which can be seen in the histograms in Figure 3. First, commute time has a very long tail to its distribution, as some drivers have very long commutes while the average is not far from zero. In order to address for this, I needed an adjustment which would create a more normal distribution but also retain the explanatory power of the people with commute times of zero, which eliminated the use of the logarithm of commute time. Instead I normalized the commute time, creating a new variable that divided the commute time by the

average commute time of the sample. This lessened the impact of outliers and made the distribution a little more normal.

For both income and housing costs, I took the natural logarithm of the sample in order to get an adjusted value for both variables. There are a many reasons to take the natural logarithm here. First, it is fairly common practice to take the logarithm of these particular values in economics research because typically helps make the data better fit a normal distribution. But there is also additionally an intuitive reason to take the logarithm of these two variables. Income and housing costs are both large sums of money that are subject to diminishing marginal utility. An additional \$100 of income will contribute a much larger increase in utility for an individual who has low income than the increase in utility that the same increase in income will have on an individual who has high income. Throughout this investigation I used both the adjusted and unadjusted core variables in my regressions in order to utilize the benefits of both sets of data and see how this change impacted the relationship with well-being and the significance of commute time.

The dependent variable that I need data for is a measure for life satisfaction or happiness. First off, this is difficult to measure. The Stutzer and Frey (2008, p. 344-345) paper used "subjective well-being" as a proxy for economic utility. This subjective well-being meant that it was an individual self-reporting their own well-being on a survey when prompted, so it was individuals judging themselves. In order to confirm that this would be an accurate proxy, they performed and researched various "validation tests" which confirmed that 1) this measure is accurate with behavior, 2) this measure is both stable yet sensitive to life changes, and 3) this measure is "interpersonally comparable." In order to show that my dependent variable can also

hold up to these tests, I will need to perform additional research and look for additional papers that look into these measures.

Unfortunately, there are no true subjective well-being measures in the NLSY79 surveys, so instead I will use another similar measurement, which is the CES-Depression score.

Conveniently, 1994 was one of the years in which this score was measured. The CES-D stands for the Center of Epidemiologic Studies Depression Scale, which was developed originally to test for depression in general population surveys, but its success led to its use as a screening instrument in primary care clinics used to measure general well-being and mental health and stability.

CES-D scores are calculated by asking a series of questions, in this particular case seven, about various symptoms of depression. The survey participants are asked how often in the past week they experienced the symptoms listed, with each one measured in "Rarely/None of the Time/1 Day", "Some/A Little of the Time/1-2 Days", "Occasionally/Moderate Amount of the Time/3-4 Days", or "Most/All of the Time/5-7 Days." Each of those answers corresponds to a score of a 0, 1, 2, or 3, respectively. The seven symptoms that the participants were asked about in 1994 were poor appetite, having trouble keeping mind on tasks, whether they felt depressed, whether everything took extra effort, restless sleep, sadness, and whether they could not keep it going. These seven scores were then added up to make up each individual's CES-D score, which could range from 0 to 21, with 0 being the least likely to be experiencing depression and 21 being the most likely. Because this scoring system is fairly counterintuitive, and it makes it simpler to understand if better off people have higher scores, I inversed the data set. This makes the best off people have 21 as their CES-D scores, and the worst off people have a score of zero.

The mean for this variable is 17.23, which seems like a reasonable level to me. The minimum and maximum fit the theoretical restriction of 0 and 21.

There are a variety of other variables mentioned in Table 1 one that are used in this investigation. First of all, as mentioned before, the range for age is only 29-37, and the average age is 32.98. This is definitely an aspect of this sample to be aware of because it will continue to differentiate many of the differences from samples and the general public throughout. There are also five dummy variables that are used to test their effects on the relationship between housing choice and well-being. Two are based on the location of the individual's residence, the central city and MSA dummy variables. A MSA is a Metropolitan Statistical Area, which is the area of urban development that surrounds a dense central city. The central city variable is defined as only individuals who live in the central city of their MSA. The central city variable showed that the percentage of the sample that lives in the central city is 15.07%. Conversely, the MSA variable indicated that 81.21% of the sample lived in a metropolitan statistical area. The next dummy variables in this experiment are race variables. The NLSY79 at this point still only clarified all of its survey participants as black, Hispanic, or not black or Hispanic. Lumping all other minority races with white causes a few issues. So the effect on these different races cannot be distinguished. These variables show that the sample is made up of 25.02% black individuals and 15.78% Hispanic individuals. This is slightly uncharacteristic of the United States population at the time. At the time of the 1990 U.S. Census, 12.1% of the U.S. population was black, and 9.0% was Hispanic (Gibson & Jung). These are higher rates of minorities than the general public. The last of the dummy variables is the child at home variable. This is pretty self-explanatory, these are people who have a child who lives in the same house as them, and so they live together at least a majority of the time. This variable shows that 55.73% of the members of the sample

have a child living with them in their home, which makes sense given the age range of our sample. On average 43.5% of American households have a child present, so it is reasonable to assume that this age range that is a major time to have children has a higher percentage of children present (Vespa, Lewis, and Kreider, 8). This is necessary because having a child effects school choices and heightens concerns about safety, further complicating the already complicated idea of housing choice.

Overall, the sample I use is younger, more urban, has a higher percentage of blacks and Hispanics, is more likely to have a child at home, has lower incomes, and owns less valuable homes that the US population in general. However none of these values are not far off from national averages, so this sample should still be fairly representative of the relationship between commuting and well-being for the general public.

	CES-D	Commute	Income	<b>Housing Cost</b>
CES-D Score (Proxy for	1.0000			
Well-Being)				
Average Daily Commute	0.0267	1.0000		
Time, One-Way				
Total Individual Annual	0.1511	0.1551	1.0000	
Income				
Market Value of Residential	0.0816	0.1273	0.3985	1.0000
Property Owned				

Figure 5: Correlations between Main Variables

Given these characteristics of the data sample used for this investigation, I will now continue on to look into the relationships between the four core variables. The correlations between the main variables reflect the fact that there are many different factors that go into well-being, so neither income or commute time have a very large correlation with CES-D scores. Commute time and CES-D have a correlation of 0.0267, which is small and positive. Based on the results of the Stutzer and Frey piece, it is safe to assume that they would have a sufficiently

large, negative correlation between commute time and well-being. I would expect, based on both the other paper and intuition, that people would be less happy the longer time they spent commuting, which would give us a negative correlation between these two variables, but this seems to indicate the opposite. There are definitely other factors at play, but this could also be an indicator that the urban layout in the United States does not allow for people to have full options at the margin on where they live. That is to say that there may be structural causes at play. However it is difficult to make assumptions without correcting for other variables, and because much of this investigation focuses on the relationship between commute time and well-being, I will discuss this much more later in the paper.

The next correlation, between income and CES-D scores, is fairly straightforward. While having greater income does not necessarily result in making individuals better off and certainly does not make them much less likely to have mental health issues, in the aggregate I don't think it is much of a surprise that people who have higher incomes are better off. In fact, if there weren't a fairly sizable positive correlation in this case, I would be immediately questioning the validity of using CES-D scores as a proxy for well-being. But there is a positive correlation; so on average well-being goes up as income increases.

Another correlation to note is between income and commute time. The correlation in this case is 0.1057, which is a decent-sized positive relationship. This reveals that this likely at least some impact on the relationship between commute time and well-being by income, so some initial regressions will provide additional insights. This also reveals a good deal about the structure of American cities. It seems odd, at least initially, that commute time increases as income increases. But there are a lot of factors that lead to this. First is the prevalence of suburbanization in the United States. When people are better off, there is a tendency to live

further away from ones place of work and from the center of a city, as people live in locations where they can have slightly more land. Another factor at play here is that people with greater incomes can afford to travel further to work, because they both have better means of transportation and are less concerned about the opportunity costs present. However, people with higher income also have a higher value of time, which would make them want to commute less. There are competing substitution effects and income effects in play here, so there are various factors on the relationship between income and commute time.

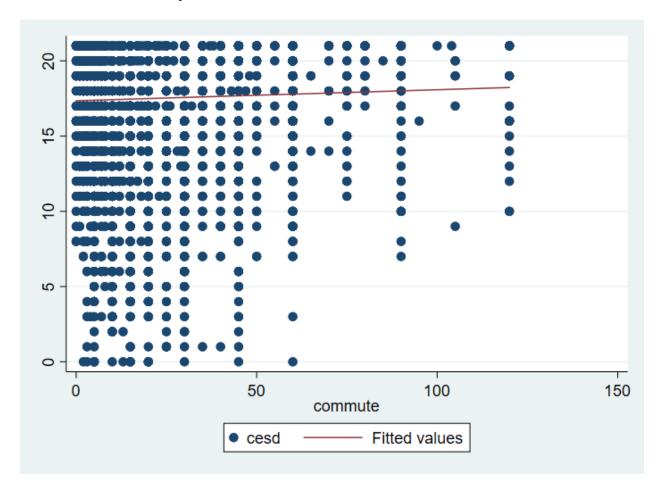


Figure 6: Scatter Plot and Trend Line for Commute Time (x-axis) and Well-Being (y-axis)

Above is a sample scatter plot with commute time as the x-axis and well-being as the y-axis, which provides some help in visualizing the data. However there are a great deal of data

points that don't make much of a distinctive shape that leads to simple understanding. The similar linear regression line between these two variables that can be seen on this graph is:

$$cesd = 0.0070793(commute) + 17.35162$$
 (2)

This shows us, like in the correlation data, that without correcting for any other variables there is a slight positive relationship between commute time and well-being.

There are two important takeaways in this chart. First is that there is a greater density of individuals near the top than near the bottom, so the top end of the data could have its tail cut off, resulting in people bunching at the 21 mark. Another key takeaway is that the commute time also has a lot of its tail cut off on one side. While commute time cannot go below zero, it can increase very far, as show by some of the outliers in the data.

The other main takeaway from Figure 6 is that it seems to show a different link between commute time and well-being than previous studies, as there seems to be a positive relationship. Controlling for more variables with explanatory power may affect this, and the regressions in the next section will provide a better understanding of this relationship.

### V. EMPIRICAL SPECIFICATION

In order to test the effects of commute time on an individual's well-being, I used a variety of different methodologies. The first methodology was to replicate that of Stutzer and Frey's investigation of German cities. In their study they used commute time, income, and housing cost as the determinants of housing choice that would influence well-being. I used these same determinants as the base variables for my first regression.

While that model has logical variables, I am unsure whether they are the best determinants for understanding housing choice. To remedy this I began investigating a large

number of other variables that I believed may provide explanatory power towards housing choice. Hopefully these new variables will present some additional insights into the choices and tradeoffs that commuters are making. I also investigated these new variables using both unadjusted and adjusted core independent variables, to see their interactions with both sets.

The main focus of these regressions is the coefficient for commute time – both whether the coefficient is negative, zero, or positive, and whether or not it passes the t-test that proves that it is different from zero with statistical significance.

If this investigation were to match what was found in the Stutzer and Frey paper, the coefficient for commute time would be negative and statistically significant. This result would show that people are worse off when they spend more time commuting, which would infer that a similar "commuting paradox" to the one that Stutzer and Frey found is present. In the case that the coefficient is significant and positive, there would still be a paradox, because the assumption is that people are optimizing based on these factors so the coefficient should be zero. Regardless, if the coefficient is zero or positive, we have a very different result than the one the Stutzer and Frey found. This would indicate that a deeper investigation is necessary to isolate the effects of commute time and to connect that with how well off the individual is, as these factors may be muddled or blocked by other variables that haven't yet been accounted for.

If the coefficient is positive, the initial conclusion that I would make is that people are not fully rational, and thus fail to recognize the impact of commute time on their lives. This is definitely a legitimate concern and something that is may be true regardless of the coefficient found. Another possibility is that there are unseen further amenities or drivers that highly correlate with commute time, and therefore the coefficient for commute time is capturing these other effects. Regardless, there are likely both economic and behavioral reasons at play.

Table 2
Regression of Impact on Well-Being Replicating Stutzer & Frey's Methodology

<u> </u>	
Variable	Coefficient
	(Std. Error)
Average Daily Commute Time, One-Way	000404
	(.0031986)
Total Individual Annual Income	.0000226***
	(.00000318)
Market Value of Residential Property Owned	.00000132
	(.000000803)
Constant	17.18359***
	(.1225312)
Observations	3,439
$R^2$	.0210
Adjusted R <sup>2</sup>	.0201

<sup>\*</sup> Significant at the 10 percent level

The regression using the Stutzer & Frey model gives very little predictive value of well-being, as indicated by its very small R<sup>2</sup> and adjusted R<sup>2</sup> values. However that is not the main focus, as what really matters is how the addition of income and housing affects the relationship between commute time and well-being. Income's coefficient is significant and easily passes its t-test. The coefficient for housing cost is not significant and does not pass the t-test. Commute time has a very small, negative coefficient, which is -0.000404. This coefficient is not significant. It seems from this regression that we cannot prove a non-zero relationship between commute time and well-being. The regression here as of now seems to show that the relationship between well-being and commute time is essentially zero, which is a very different than what Stutzer and Frey found. They found a significantly negative coefficient, which was not consistent with optimization. This result on the other hand cannot be proven to be statistically significant from zero, and is not close to statistical significance, so there is not any evidence against optimization.

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

A better way to understand these results is to utilize the regression to find the equivalent valuation. These units of well-being have little inherent meaning, so it is helpful to convert them into a unit that is easily understood, US dollars. The question that is asked is, how much money would someone who does not commute to work have to be paid in extra annual income in order to commute the average value of 21.09 minutes to work each day and be just as well-off? In this case, the equivalent valuation is \$377.31, meaning that in a year the time that an individual spends commuting on average is worth that much. This is not saying that this is the value of their time as in their hourly wages, but instead saying that this is what they would have to receive to be equally well-off if they went from not commuting to an average commute. This annual cost of \$377.31 is the 1.93% average income of the average person from the sample, compared to the same number being 35.4% for Stutzer and Frey's paper.

Table 3
Regression of Impact on Well-Being with Squared Commute Term

Regression of Impact on Well-Being with Squared Commute Term				
Variable	Coefficient			
	(Std. Error)			
Average Daily Commute Time, One-Way	.0006276			
	(.005992)			
Average Daily Commute Time, One-Way, Squared	0000116			
	(.0000568)			
Total Individual Annual Income	.0000225***			
	(.00000319)			
Market Value of Residential Property Owned	.00000139			
	(.000000803)			
Constant	17.17266***			
	(.1337881)			
Observations	3,439			
$R^2$	.0210			
Adjusted R <sup>2</sup>	.0199			

<sup>\*</sup> Significant at the 10 percent level

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

The third regression undertaken was similar to the base regression, but a squared term was added to see if a quadratic better fit the data than a linear line. The result was that it didn't make a large different. The significant coefficients from the previous two regressions stayed the same while the coefficients that were not significant stayed that way too. The one interesting aspect of this regression is that the coefficient of the first commute term is now positive, and the coefficient of the squared term is negative, give the model a downward facing, downward sloping arc as its trend line. This would imply that instead of longer commutes making you worse off, it actually makes you better off at first, before making you worse off as you got to extremely long commutes. This is slightly less logical, but still makes sense, as it is fair to assume that housing quality may be better slightly further from your place of work as you get more choices. The equivalent valuation in this case is -\$364.124, as according to this model people who don't commute are worse off than those two do, so to be equally happy when increasing their commute from zero to the average commute time, these people would be paid less income. However, the coefficients for commute time both remain insignificant.

It is also important to note that the coefficients for income and housing costs are almost unchanged from the previous regression. This means that there is no omitted variable bias present, meaning that using the squared term gives little to no additional explanatory power. Because of this result, I will not be using the squared term in the rest of the regressions, but instead just use the unadjusted and adjusted linear variables for commute time.

 Table 4

 Regression of Impact on Well-Being with Adjusted Independent Variables

Variable	Coefficient
	(Std. Error)
Normalized Average Daily Commute Time,	.0162132
One-Way	(.0691755)
Natural Logarithm of Total Individual Annual	.4459201***
Income	(.0694995)
Natural Logarithm of Market Value of	.2701918***
Residential Property Owned	(.0719453)
Constant	10.44214***
	(.8957419)
Observations	3,292
$R^2$	.0231
Adjusted R <sup>2</sup>	.0222

<sup>\*</sup> Significant at the 10 percent level

This regression follows the same format as the first but takes the adjusted values for the independent variables in an attempt to reduce the effects of the outliers and super-commuters on the core of the data. Other than that, the methodology behind this regression is the same as the first. The results of this regression are about the same as the first as well. The coefficient for commute time is slightly positive this time, but still not significant. The coefficient for income is significant, and the R<sup>2</sup> values remain low. The major change that this provides is that the housing cost coefficient is now statistically significant at the 1 percent level, a major change from the previous regressions. The equivalent valuation in this case is -\$723.294, which is larger in absolute value than that of the previous two regressions.

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

Table 5
Regression of Impact on Well-Being with Central City Term

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	0002256	.0186476
	(.0032336)	(.0700426)
Total Individual Annual Income	.0000227***	.4379258***
	(.00000323)	(.0702436)
Market Value of Residential Property Owned	.00000118	.2600398***
	(.000000827)	(.0727836)
Current Residence in Central City of MSA	3598647*	2700174
	(.2181803)	(.2216791)
Constant	17.24168***	10.67669***
	(.1252841)	(.9061258)
Observations	3,301	3,166
$R^2$	.0215	.0226
Adjusted R <sup>2</sup>	.0203	.0214

<sup>\*</sup> Significant at the 10 percent level

After using the basic format the Stutzer and Frey outlined, I shifted to look into a variety of other variables to test how they provide explanatory power towards the relationship between commute time and well-being. First, I tried using a dummy variable for whether or not people's residence was in the central city of a MSA. For this test, as for all the ones that follow, I performed each regression as adjusted and unadjusted, where the adjusted one has the normalized commute time and uses the natural logarithms of the income and the housing cost variables, while the unadjusted regression uses their raw values. While the other coefficients were about the same as they usually are, with the commute coefficient returning to a slight negative in the unadjusted test, the city dummy variable was slightly significant on that side as well. The coefficient for the city dummy variable was a larger negative value, indicating that living in a city on average makes you worse off than those who do not. The equivalent valuation for commuting on the unadjusted side, similar to before, was \$209.613. On the adjusted side,

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

the equivalent valuation is -\$849.739. Both of these seem to be in line with previous regressions. Even though this adds a slightly significant term, it doesn't change much in the results.

When comparing the unadjusted and adjusted results, the coefficients themselves should not be compared because they have been transformed by different functions. The two things that should be compared are the sign of the coefficient and whether or not it is significant. The major differences between unadjusted and adjusted in this test are that the city term is significant, though just slightly, in the unadjusted regression. The housing coefficient is significant as it typically is with the adjusted regressions.

Table 6
Regression of Impact on Well-Being with MSA Term

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	0001409	.0224919
	(.0032309)	(.0699617)
Total Individual Annual Income	.0000234***	.4530971***
	(.00000324)	(.0703418)
Market Value of Residential Property Owned	.00000160*	.3159274***
	(.000000839)	(.0749355)
Current Residence in MSA	4304042***	4798534***
	(.1473549)	(.1531463)
Constant	17.48550***	10.24959
	(.154829)	(.915474)
Observations	3,301	3,166
$R^2$	.0232	.0252
Adjusted R <sup>2</sup>	.0220	.0240

<sup>\*</sup> Significant at the 10 percent level

Next, I tried using a similar dummy variable but this time looking at whether their current residence was in a MSA at all, regardless of whether or not it was in the central city of the MSA. This resulted in a similar, but more significant coefficient. Otherwise, the coefficients

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

and R<sup>2</sup> values are very similar to those of the city dummy variable. The equivalent valuation in this case for unadjusted is \$126.999, so quite small. On the other hand, for the adjusted regression it is -\$994.130. The coefficient for commute time is very close to zero in this regression in both the unadjusted and adjusted regressions.

**Table 7**Regression of Impact on Well-Being with Age Term

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	0003958	.0162262
	(.0031992)	(.0691849)
Total Individual Annual Income	.0000226***	.4460939***
	(.00000318)	(.0695111)
Market Value of Residential Property Owned	.00000131	.2683776***
	(.000000805)	(.0721756)
Age	.007009	.0086244
	(.0263898)	(.0267968)
Constant	16.95211***	10.17412***
	(.8801188)	(1.223139)
Observations	3,439	3,292
$R^2$	.0210	.0231
Adjusted R <sup>2</sup>	.0199	.0219

<sup>\*</sup> Significant at the 10 percent level

In a regression that takes on a different direction, I added an age term to see how that would affect the results. Though the total age range for the group is only eight years, I still thought that this might give some interesting outcomes. For instance, perhaps people at higher age ranges are less likely to be affected by commute times because they are more likely settled down and in a home they enjoy.

The results seem to slightly match that hypothesis. Both coefficients for commute time are almost exactly zero, and the coefficient for the age term is positive, albeit small. This also says that people are better off as they get older, which is an interesting result, especially since

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

we have such a small age range in this sample. If we had a wider range how would that change the results?

Table 8
Regression of Impact on Well-Being with Dummy Variables for Race

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	.0002402	.0270233
	(.0032014)	(.0692002)
Total Individual Annual Income	.0000221***	.4400665***
	(.00000318)	(.0695525)
Market Value of Residential Property Owned	.00000105	.2423369***
	(.000000810)	(.0728617)
Black	4304919***	4245256***
	(.1612091)	(.1647127)
Hispanic	3891803**	3385741**
	(.159146)	(.1623154)
Constant	17.34784***	10.93113***
	(.132132)	(.9102089)
Observations	3,439	3,292
$R^2$	.0241	.0258
Adjusted R <sup>2</sup>	.0227	.0243

<sup>\*</sup> Significant at the 10 percent level

In this regression, I used two dummy variables for race to break apart the three values that the NLSY79 had for race, which were Black, Hispanic, and Not Black or Hispanic. The results for this regression were especially interesting. First off, the dummy variables for both Black and Hispanic were negative and significant, showing that on average, correcting for income and housing cost, these people are still worse off than people who are not Black or Hispanic. Both coefficients for commute time are also positive in this regression, showing that for people who are not Black or Hispanic, people are on average better off the longer their commute is, and the longer they live from their place of work. The equivalent valuation in this case is for unadjusted is -\$229.237 and is -\$1237.11 for the adjusted, because the individual

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

would be better off according to the model if their commute time increased. It is also worth noting that in these two regressions are very similar despite one being adjusted to create a more normal distribution.

 Table 9

 Regression of Impact on Well-Being with Dummy Variable for Child at Home

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	0001866	.0209935
	(.0032711)	(.0707881)
Total Individual Annual Income	.0000223***	.4461901***
	(.00000320)	(.0705304)
Market Value of Residential Property Owned	.00000137*	.2675742***
	(808000000.)	(.0727036)
Child at Home	0101628	.0012608
	(.1267689)	(.129404)
Constant	17.1988***	10.4704***
	(.1556446)	(.9155677)
Observations	3,439	3,256
$R^2$	.0210	.0229
Adjusted R <sup>2</sup>	.0199	.0217

<sup>\*</sup> Significant at the 10 percent level

Another regression that I attempted was seeing the effect of having a child living at home had on behavior. The NLSY79 has good data on where the survey taker's children live, so these are only the ones that have their own children living at their house. To clarify, this a dummy variable, not the number of children they have living at home. Having a child living at home in theory would impact housing choices, making these individuals have higher considerations of schools and safety in deciding where to live. In reality, it seemed that this actually had little effect on the results. The coefficients and their significance looked the same as most of these regressions, and the unadjusted dummy variable for children was not significant and slightly negative. The equivalent valuation in the unadjusted case was \$176.486, which is one of the

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

smaller values that we have had. On the other side, the adjusted case had slightly positive but not significant coefficients for both commute time and children at home, so that case implies that people are happier if they have children at home, but this is not significant so it is not really possible to assign meaning. The equivalent valuation for the adjusted case is -\$941.036, a fairly average adjusted valuation.

Table 10
Regression of Impact on Well-Being with All Tested Variables

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	.0006815	.0374924
	(.0033124)	(.0717586)
Total Individual Annual Income	.0000226***	.4493923***
	(.00000327)	(.0715013)
Market Value of Residential Property Owned	.00000126*	.2727613***
	(.000000857)	(.0772415)
Current Residence in City	1819064	0772305
	(.2237767)	(.2274822)
Current Residence in MSA	3334621**	3882377**
	(.1520346)	(.1580367)
Age	.0131862	.0163654
	(.0269647)	(.0273694)
Black	3809956**	3361712**
	(.1654638)	(.1691329)
Hispanic	2143818*	1725693
	(.1652266)	(.1683702)
Child at Home	-0.173192	.0112912
	(.1295343)	(.1322985)
Constant	17.14685***	10.239***
	(.901203)	(1.266775)
Observations	3,263	3,130
$R^2$	.0250	.0265
Adjusted R <sup>2</sup>	.0223	.0237

<sup>\*</sup> Significant at the 10 percent level

After I tested out that variety of variables, I decided to make the best model possible by taking the variables that had the most explanatory power. The first step in this was to put all of

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

the variables that I tested into one regression for unadjusted and one for adjusted, (Table 10) to see which of these variables are significant and give meaning to the function. Aside from the coefficients for income and housing, the only coefficients that were significant in both unadjusted and adjusted were that of the MSA dummy variable and that of the black one. In order to see if any of these coefficients that were not significant on their own were jointly significant, I ran an F-Test. The test was not significant, so the other variables were determined not to be significant and would not be used in the final model.

**Table 11**Regression of Impact on Well-Being with Significant Variables

Variable	Unadjusted	Adjusted
	Coefficient	Coefficient
	(Std. Error)	(Std. Error)
Average Daily Commute Time, One-Way	.0003039	.0297853
	(.0032345)	(.0700011)
Total Individual Annual Income	.0000233***	.455038***
	(.00000324)	(.0703061)
Market Value of Residential Property Owned	.00000130*	.2864933***
	(.000000848)	(.0761066)
Current Residence in MSA	4000503***	449077***
	(.1478485)	(.1537102)
Black	366503**	35324**
	(.1592632)	(.1625623)
Constant	17.54772***	10.58962***
	(.1570723)	(.9282207)
Observations	3,301	3,166
$R^2$	.0247	.0267
Adjusted R <sup>2</sup>	.0233	.0251

<sup>\*</sup> Significant at the 10 percent level

Taking the significant variables from the previous regression, the result is the core three impendent variables in addition two the variables for black individuals and those who live in an MSA. The results from these two regressions both got the biggest  $R^2$  of any of the regressions in

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

their respective types, and a variety of different variables all affecting each other. All of the variables remain significant in this regression as well. The equivalent valuation for the unadjusted regression is -\$1558.86, meaning that just to increase one's commute from 0 to 22 minutes would make them equally well off even if you took off \$1558.86 from their income. That's 7.98% of the average annual income, a large amount. In addition, the equivalent valuation for the adjusted regression is -\$1321.39, which is the second highest absolute value of any of the equivalent valuations, only second to the adjusted regression with all of the tested variables. However, the key take away here is that the commute time variable is still insignificant (Table 11). Even taking into account only the significant variables does not give credence to the theory that commuters are not optimizing.

# VI. CONCLUSION

There were many regressions tested to see if and how they could help explain the relationship between commuting and well-being, and these investigations shed a lot of light on the complexity of this relationship. One of the main goals of this paper was to replicate the methodology of Stutzer and Frey's paper and see if I found a significant, negative coefficient for commuting that unequivocally shows that people are failing to optimize for their well-being. I did not find that this was the case in the United States; instead, I found a large amount of evidence that shows that this is not the case. Throughout all of my tests, I never once found a coefficient for commuting that was significantly different than zero, and most p-values were not even close. The closest p-value was 0.601, which was the adjusted regression with every variable included. Overall, I found no evidence that people are failing to optimize for commute time.

Table 12
Unadjusted Equivalent Valuation/Compensation for Regressions

Regression	Commute	Equivalent Valuation/	Percentage of Annual	
	P-Value	Compensation	Average Income	
Base	0.900	\$377.03	1.93%	
Squared Term	0.917	-\$364.124	1.86%	
City Term	0.944	\$209.613	1.07%	
MSA Term	0.965	\$126.999	0.65%	
Race Term	0.940	-\$229.237	1.17%	
Child at Home	0.955	\$176.486	0.90%	
All Variables	0.837	-\$636.007	3.26%	
Significant Variables	0.925	-\$287.429	1.47%	

 Table 13

 Adjusted Equivalent Valuation/Compensation for Regressions

rajusted Equivalent valuation, compensation for regressions								
Regression	Commute	Equivalent Valuation/	Percentage of Annual					
	P-Value	Compensation	Average Income					
Base	0.815	-\$723.294	3.70%					
City Term	0.790	-\$849.739	4.35%					
MSA Term	0.748	-\$994.130	5.09%					
Race Term	0.696	-\$1237.11	6.33%					
Child at Home	0.767	-\$941.036	4.82%					
All Variables	0.601	-\$1699.59	8.70%					
Significant Variables	0.671	-\$1321.39	6.76%					

When looking at Table 12 and Table 13, there are multiple trends present. First, the adjusted values are much more clustered and similar, partially a result of their narrow, normal distributions. All of the adjusted commute time coefficients were positive, so all of their equivalent valuations were negative. For the unadjusted value's coefficient for commuting, they straddle zero, with four above zero and four below. This makes it very clear that the value is not significant. Additionally in the unadjusted regressions the equivalent valuations are all lower in absolute value than all of the equivalent valuations in the adjusted regressions.

Overall, between the 15 regressions, the range of equivalent valuations goes from \$377.03 to -\$1699.59. None of these values are very large, with the highest percentage of annual income of any equivalent valuation being 8.70%. And because that is full of all of the

variables one could argue that is not a fair comparison, so the highest normal regressions would be the adjusted significant variables regression with 6.76%. To compare, Stutzer and Frey's result from their study was that one would have to pay 35.4% as their equivalent evaluation, which is over five times larger than the result that I found for the United States (Stutzer & Frey, 355). The result that was found in Germany is much larger, explaining why is was significant and the United States was not very close. The 35.4% that Germany found shows a major impact on the economy, while the U.S. example is not nearly as extreme.

Overall, there is no Commuting Paradox in the United States, so I find no evidence consistent with Stutzer and Frey's results. My results found that the coefficient for commuting was never significant, and that any values that were found were minuscule in comparison to the size of the paradox that Stutzer and Frey found. My hope is that this paper will have better improved the understanding of the relationship between commute time and well-being, and how that decision affects housing choice.

### **APPENDIX**

Table 14

Summary Table of All Unadjusted Regressions Squared MSA Age Term Child at Base City Race Term Term Home Term Coefficie Coefficie Coefficie Coefficie Coefficie Coefficie Variable Coefficie nt nt nt nt nt nt nt (Std. (Std. (Std. (Std. (Std. (Std. (Std. Error) Error) Error) Error) Error) Error) Error) Average -.000404 .0006276 -.0002256 -.0001409 -.0003958 .0002402 -.0001866 Daily (.0031986)(.005992)(.0032336)(.0032309)(.0031992(.0032014)(.0032711)Commute ) ) ) ) ) ) Time, One-Way Total .0000226 .0000225 .0000227 .0000234 .0000226 .0000221 .0000223 \*\*\* \*\*\* \*\*\* \*\*\* \*\*\* \*\*\* \*\*\* Individua (.00000311 Annual (.0000031(.0000032(.0000032)(.0000031(.0000031(.0000032)Income 3) 8) 9) 4) 8) 8) 0) Market .0000013 .0000013 .0000011 .0000016 .0000013 .0000010 .0000013 0\* 7\* Value of 9 8 5 2 Residenti 8000000.) (.0000008 (.0000008 8000000.) (.0000008 (.0000008 (.0000008 al 03) 03) 27) 39) 05)10) 08)**Property** Owned Child at N/A -.0000116 .007009 -.0101628 Home (.0000568).3598647 .4304042 (.1267689)(.0263898)\*\*\* ) ) ) (.2181803)(.1473549)17.24168 17.48550 Constant 17.18359 17.17266 16.95211 17.34784 17.1988\* \*\*\* \*\*\* \*\*\* \*\*\* \*\*\* (.1225312)(.1337881(.1252841)(.154829)(.8801188)(.132132)(.1556446)3,439 3,301 3,439 Observati 3,439 3,301 3,439 3,439 ons  $R^2$ .0210 .0210 .0215 .0232 .0210 .0241 .0210 .0201 .0199 .0199 .0199 Adjusted .0203 .0220 .0227  $R^2$ 

<sup>\*</sup> Significant at the 10 percent level

<sup>\*\*</sup> Significant at the 5 percent level

<sup>\*\*\*</sup> Significant at the 1 percent level

**Table 15**Summary Table of Unadjusted Regressions with Significance at 10% Confidence Level

	Base	Squared	City	MSA	Age	Race	Child at
		Term	Term	Term	Term		Home
Variable	Coefficie						
	nt						
	(Std.						
	Error)						
Average	000404	.0006276	-	-	-	.0002402	-
Daily	(.003198)	(.005992)	.0002256	.0001409	.0003958	(.003201	.0001866
Commute	6)		(.003233)	(.003230	(.003199)	4)	(.003271)
Time, One-			6)	9)	2)		1)
Way							
Total	Yes						
Individual							
Annual							
Income							
Market	No	No	No	Yes	No	No	Yes
Value of							
Residential							
Property							
Owned							
Added	N/A	No	Yes	Yes	No	Yes/Yes	No
Term(s)							
Constant	Yes						
Observatio	3,439	3,439	3,301	3,301	3,439	3,439	3,439
ns							
$R^2$	.0210	.0210	.0215	.0232	.0210	.0241	.0210
Adjusted	.0201	.0199	.0203	.0220	.0199	.0227	.0199
$R^2$							

### Works Cited

- Clark, William A.V., Youqin Huang, Suzanne Withers. (2003). Does commuting distance matter?. *Regional Science and Urban Economics*, 33(2). Pages 199-221, ISSN 0166-0462, <a href="http://dx.doi.org/10.1016/S0166-0462(02)00012-1">http://dx.doi.org/10.1016/S0166-0462(02)00012-1</a>. (<a href="http://www.sciencedirect.com/science/article/pii/S0166046202000121">http://www.sciencedirect.com/science/article/pii/S0166046202000121</a>)
- Dill, J., & Carr, T. (2003). Bicycle Commuting and Facilities in Major U.S. Cities: If You Build Them, Commuters Will Use Them. *Transportation Research Record: Journal of the Transportation Research Board*, 1828, 116-123. doi:10.3141/1828-14
- Gibson, C., & Jung, K. (2005, February). *Historical Census Statistics On Population Totals By*Race, 1790 to 1990, and By Hispanic Origin, 1970 to 1990, For Large Cities And Other

  Urban Places In The United States(United States, U.S. Census Bureau, Population

  Division). Retrieved from

  https://www.census.gov/population/www/documentation/twps0076/twps0076.pdf
- Hamilton, B., & Röell, A. (1982). Wasteful Commuting. *Journal of Political Economy*, *90*(5), 1035-1053. Retrieved from http://www.jstor.org/stable/1837132
- Ihrke, D. K., Faber, C. S., & Koerber, W. K. (2011). Geographical mobility: 2008 to 2009(United States, U.S. Census Bureau). Washington, DC: U.S. Dept. of Commerce, Economics and Statistics Administration, U.S. Census Bureau. Retrieved from <a href="https://www.census.gov/prod/2011pubs/p20-565.pdf">https://www.census.gov/prod/2011pubs/p20-565.pdf</a>
- In Most States, a Spike in 'Super Commuters'. (n.d.). Retrieved October 1, 2017, from <a href="http://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2017/06/05/in-most-states-a-spike-in-super-commuters">http://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2017/06/05/in-most-states-a-spike-in-super-commuters</a>
- Ingraham, C. (2016, February 25). The astonishing human potential wasted on commutes.

- Retrieved October 2, 2017, from
- https://www.washingtonpost.com/news/wonk/wp/2016/02/25/how-much-of-your-life-youre-wasting-on-your-commute/?utm\_term=.13410e6307a5
- Levinson, D., & Wu, Y. (2005). The rational locator reexamined: Are travel times still stable? *Transportation*, 32(2), 187-202. doi:http://dx.doi.org/10.1007/s11116-004-5507-4
- Lundberg, G. A., Komarovsky, M., & McInerny, M. A. (1992). *Leisure: A suburban study*. Ann Arbor, MI: UMI.
- McKenzie, B. (2013). *Out-of-State and Long Commutes: 2011* (Rep.). American Community Survey. https://www.census.gov/content/dam/Census/library/publications/2013/acs/acs-20.pdf
- Moss, M. L., & Qing, C. (2012, February). *The Emergence of the "Super-Commuter"* [Scholarly project]. In *New York University Wagner School of Public Service*. Retrieved September 28, 2017, from <a href="https://wagner.nyu.edu/files/rudincenter/supercommuter\_report.pdf">https://wagner.nyu.edu/files/rudincenter/supercommuter\_report.pdf</a>
- Morrison, P., & Abrahamse, A. (1983). Is Population Decentralization Lengthening Commuting Distances? *Population Research and Policy Review, 2*(2), 189-206. Retrieved from <a href="http://www.jstor.org/stable/40229923">http://www.jstor.org/stable/40229923</a>
- Nelson, G. D., & Rae, A. (2016). An Economic Geography of the United States: From Commutes to Megaregions. *Plos One*, *11*(11). doi:10.1371/journal.pone.0166083
- So, K., Orazem, P., & Otto, D. (2001). The Effects of Housing Prices, Wages, and Commuting

  Time on Joint Residential and Job Location Choices. *American Journal of Agricultural Economics*, 83(4), 1036-1048. Retrieved from http://www.jstor.org/stable/1244712

- Stutzer, A., & Frey, B. (2008). Stress That Doesn't Pay: The Commuting Paradox. *The Scandinavian Journal of Economics*, 110(2), 339-366. Retrieved from <a href="http://www.jstor.org/stable/25195346">http://www.jstor.org/stable/25195346</a>
- Sultana, S., & Weber, J. (2007). Journey-to-Work Patterns in the Age of Sprawl: Evidence from Two Midsize Southern Metropolitan Areas. *The Professional Geographer*, *59*(2), 193-208. doi:10.1111/j.1467-9272.2007.00607.x
- United States Census Bureau. (n.d.). Commuting (Journey to Work). Retrieved September 7, 2017, from https://www.census.gov/topics/employment/commuting.html
- US Census Bureau. (n.d.). Historical Income Tables: People. Retrieved from https://www.census.gov/data/tables/time-series/demo/income-poverty/historical-income-people.html
- Vespa, J., Lewis, J. M., & Kreider, R. M. (august 2013). America's Families and Living Arrangements: 2012. *U.S. Census Bureau*. Retrieved from <a href="https://www.census.gov/prod/2013pubs/p20-570.pdf">https://www.census.gov/prod/2013pubs/p20-570.pdf</a>
- White, M. (1988). Urban Commuting Journeys Are Not "Wasteful". *Journal of Political Economy*, *96*(5), 1097-1110. Retrieved from http://www.jstor.org/stable/1837250