Happiness and Traffic: An Analysis of Long Term Effects

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Abstract

Traffic has a profound effect on how humans perceive their own happiness. What remains to be seen, however, is whether the short term happiness losses associated with traffic lead to lower overall happiness for people living in areas with consistently high traffic. This paper looks at average traffic delays in major metropolitan cities in the United States and compares these delays to average happiness indices for each city. It is seen that traffic does have a measurable negative effect on a city's overall happiness, but this effect is very small and does not account for much of the variation in city happiness.

I. Introduction

For those living and working in urban and metropolitan communities traffic is all but inescapable. With the growth of urban centers and ever increasing populations traffic plays a significant and sometimes expanding role in people's lives. Greater time spent on one's commute means lost time that one could have spent with family and friends, engaging in physical activity, or participating in activities one finds relaxing. Increased commute lengths could mean higher levels of stress and a regular sense of feeling hurried, particularly for commuters with lower-income jobs or stricter work schedules. While there may be positive aspects to commuting, including extra alone time to think, listen to music, or generally unwind at the end of the day, traffic greatly affects the way people can schedule their days and manage their time, likely having significant effects on people's happiness or relative well-being. While traffic and commuting likely have negative effects on well-being, there are many factors that affect happiness, and it is important to discern if traffic alone can have a determining effect on people's well-being from one metropolitan area to the next.

Irrespective of other factors, the goal of this research is to measure if traffic in a metropolitan area has a significant correlation with levels of personal happiness, as determined from measures of self-reported well-being. We predict that the measure of traffic within a city will negatively correlate with measures of well-being. As part of this we will consider several other factors that may have effects on people's well-being within metropolitan areas, such as the number of individuals living below the poverty line, local crime rates, relative income levels, and weather patterns. This research will contribute to a greater understanding of the effects of commuting on people's relative well-being and perhaps emphasize the importance metropolitan areas must place on measures to alleviate traffic within their centers.

II. Literature Review

Many studies have been conducted on the effect traffic has on people living in cities. One subject that has been studied well is whether commuters are fully compensated for their lost time in traffic. Different measures of well-being, including self-reported health and self-reported disability, have been compared to travel mode and travel time for both commuters and non-commuters. Compared with non-commuters the report found that on average commuters were "less satisfied with their lives", and reported less happiness and higher anxiety. It has been found that with each additional minute a person commutes, they are expected to experience a decrease in happiness/satisfaction and an increase in anxiety levels (ONS 2014). This suggests that higher levels of traffic will lead to unhappier cities.

Semi-random variation in daily traffic has been correlated with self-reported happiness and used to show that on days where there is more traffic, all citizens are likely to be less happy. Every week in Beijing, a certain set of license plates based on the ending digit are banned from traveling within the city center to cut down on traffic demands. Normally, this would remove 1/5th of the cars from the roads in the city center, however because the number 4 is superstitious in China, there are many fewer cars that end in 4 than other numbers. Therefore, on days where the number 4 is banned it is seen that there are more cars on the road than on the other four days of the week. Because the day that each tail number banned rotates throughout the month, researchers were able to assemble a quasi-random dataset where certain days were guaranteed to have more traffic. This data was confirmed using day by day pollution data taken from within the city center of Beijing. Using this traffic data and daily self-reported happiness studies, the researchers were able to draw a strong correlation between daily traffic and expected happiness. It was found for each 15% increase in traffic (i.e. 5mph slower approx.) there was a 1.5% decrease in a person's happiness. This statistic remains robust when including weather, pollution levels, and excluding holidays from the data. While this does not show that on the macro level general congestion indices will correlate with general happiness indices, it does show that there is a measurable effect on individual happiness that comes from sitting in traffic (Anderson et. al. 2016). It remains to be seen whether a metro area will experience a permanent depression in happiness as a result of high traffic.

Adults in Basel, Switzerland have been studied to measure the relationship between road traffic, noise exposure, annoyance caused by noise sources, and health factors that could be effected by traffic. Noise annoyance was evaluated using a four-points Likert scale (categories: "no", "slight", "considerable", and "heavy"). The research shows that people felt a more pronounced annoyance from road, industry, and neighborhood noise over railway and aircraft noise. Significant association was found between road traffic noise and objective sleep parameters, but there was not a significant association between road traffic noise and subjective sleep quality measures, after controlling for other factors. People are shown to be unaware of the objective effects of noise on their sleep, though this may have further implications for other health risks such as cardiovascular disease despite the fact that they do not realize it, and calls into question the accuracy of "annoyance" as an indicator for certain health effects of noise (Vienneau et. al. 2014).

The NBER paper "Unhappy Cities" contains a dataset that will be useful for our research, as well as important research on happiness in major US cities and factors that correlate with them. A happiness index has been generated that includes all major metropolitan areas in the United States. This data was analyzed to look for differences in happiness across metropolitan areas and how these happiness levels changed over time. There is a significant difference between levels of happiness in different metropolitan areas and happiness behaves differently with time depending on each city. These differences persisted even after controlling for income, weather, and inequality. This research also found that there is a negative correlation between income and happiness, i.e. happier metropolitan areas have lower median incomes. It is speculated that higher incomes in unhappy places compensate for the fact that the locations aren't good for the resident's happiness. Higher incomes may be necessary to support the other ambitions of people who choose to live in unhappy cities even though they may be happier elsewhere. It is also seen that there is a positive correlation between population decline and unhappiness. For our research, this would suggest that traffic may actually positively correlate with happiness because cities with higher population growth are more likely to have high stress on their road network (Glaeser et. al. 2016). This is contrary to the intuitive idea that because traffic decreases individual happiness, traffic will also decrease citywide happiness.

Our research will expand on existing research to provide an analysis of how permanent differences in traffic effect peoples self-reported happiness. All of the papers showed that there is a strong negative correlation between traffic and happiness, however this does not necessarily mean that cities as isolated units will be more or less happy than other cities based purely on their traffic. Because cities that are growing have higher rates of happiness, traffic may end up positively correlating with happiness. A result like this would not disprove existing research of traffic effects, but it would show that traffic is not a major indicator of whether an area has happy people or not. Our research will attempt to apply the concepts learned from earlier papers and apply them across space to look for permanent differences in happiness as a result of traffic.

III. Data

The dependent variable for this regression model is happiness. This data comes from a study by Glaeser, Ziv and Gottlieb published by the Journal of Labor Economics (Glaeser et. at. 2016). This paper uses self-reported survey data on subjective well-being from across the United States, as well as the work of Oswald and Wu, and data from the Center for Disease Control and Prevention (CDC). The survey used from the CDC is the Behavioral Risk Factor Surveillance System, a self-reporting survey. The authors modified the original data and scaled the responses 1-4, 4 representing "very satisfied" and 1 as "very dissatisfied". The authors manipulate the data in several ways to reduce the bias that may occur from differences in geography, demographics and variability in different individuals measures of happiness. They use the data from the CDC as well as the National Survey of Families and Households (NSFH). The survey is also self-reported with questions regarding well-being having a scale of 1-7. The authors use several different methods to manipulate the data to account for variations that are likely to be attributed to personal tastes rather than circumstances. This regression model will use the raw data Glaeser, Ziv, and Gottlieb compiled using the different self-reported survey data.

This report will look at data on 27 major metropolitan cities in the U.S. to see if there is a significant correlation between levels of self-reported happiness and time spent in traffic. The independent variable this paper looks at is traffic, specifically, total delay per year in hours by city (INTRIX 2016). This study is done annually by INRIX. The most available data from INRIX is the the "Worst Corridor" analysis which provides a breakdown of different metro cities in the U.S. This data set provides a breakdown in distance, time, and peak times, and free flow times. INRIX also provides a calculated "time wasted in traffic annually" estimate, however it is only for the top ten "most congested" cities in the U.S.

Other independent variables included in the regression include percentage of individuals living below the poverty line by city. This variable is likely correlated to levels of wellbeing, but not likely correlated to the average amount of time spent in traffic. This data comes from the United States Census (US Census Bureau). Income per capita (USD) is another independent variable. Data statistics on income are sourced from the United States Census. Income is primarily positively associated with happiness but may also have a correlation with time spent in traffic. Crime rates are likely to have a negative correlation with happiness, but are not likely to have a correlation with the average amount of time spent in traffic. The crime statistics come from the U.S. Department of Justice. The data is total violent offenses reported per 100,000 people. The offenses that fall under violent crime include; rape, murder, and robbery. The model will also include the average percentage of days annually that are either cloudy or partly cloudy. The amount of sunshine is likely positively correlated with levels of happiness, but is not likely to have any correlation with time spent in traffic. This data comes from the U.S. National Oceanic and Atmospheric Administration. For each city the data has been collected over periods of time ranging from 30 to 60 years. Table 3.1 below shows the data we used in our analysis. Table 3.2 contains the descriptive statistics.

Table 3.1: Data Summary

City	Total Annual Delay (hours)	Raw Happiness Score	Adjusted Happiness	Per Capita Income USD		% of Indv living below poverty line	Violent Crimes per 100,000 Residents	% of Days Cloudy or Partly Cloudy
Atlanta	179	0.0425085	20.12084	$	36,936.00	23.8	1,227	69.9
Austin	189	0.0341354	19.28353	$	34,140.00	18.5	396	69
Boston	290	-0.0385937	12.01062	$	36,395.00	22.6	726	73.2
Chicago	567	-0.0182825	14.04174	$	29,015.00	22.0	884	77.0
Cincinnati	52	-0.0469198	11.17801	$	25,683.00	30.0	905	77.8
Dallas-Fort Worth	332	0.0239839	18.26838	$	28,771.00	24.5	665	63.0
Denver	66	0.0487683	20.74682	$	35,967.00	15.7	599	68.5
Detroit	14	-0.1103486	4.83513	$	14,810.00	39.3	1,989	79.5
Honolulu	103	0.0424822	20.11821	$	31,553.00	11.8	359	75.3
Houston	309	0.0415933	20.02932	$	28,725.00	22.4	991	75.3
Kansas City	7	0.0354542	19.41541	$	26,998.00	17.8	1,251	67.1
Las Vegas	7	-0.0648205	9.38794	$	24,696.00	17.3	841	43
Los Angeles	1821	-0.0944536	6.42463	$	29,195.00	22.4	491	59.8
Miami-Fort Lauderdale	133	-0.0298883	12.88116	$	22,564.00	26.2	1,060	79.7
Minneapolis	106	0.0634182	22.21181	$	31,764.00	23.2	1,011	74.0
Nashville	15	0.0548345	21.35344	$	28,102.00	20.2	1,122	72.0
New Orleans	24	0.0144658	17.31657	$	28,668.00	27.8	974	72.3
New York	910	-0.1586999	0.0001	$	32,910.00	20.9	597	70.8
Orlando	41	0.0408762	19.95761	$	26,026.00	18.8	901	74
Philadelphia	135	-0.0779126	8.07873	$	23,302.00	26.0	1,021	74.5
Pittsburgh	62	-0.0950892	6.36107	$	27,367.00	23.8	798	83.8
San Antonio	18	0.0286772	18.73771	$	22,823.00	21.0	539	72
San Diego	61	0.0137179	17.24178	$	34,727.00	15.7	381	60.0
San Francisco	258	-0.0324222	12.62777	$	51,727.00	12.0	795	56.2
Seattle	314	0.0054195	16.41194	$	45,688.00	14.4	603	84.2
St. Louis	4	-0.0843325	7.43674	$	22,760.00	28.5	1,679	72.4
Tampa	29	0.0008184	15.95183	$	30,474.00	20.4	582	73

Table 3.2: Descriptive Statistics

	Mean	*Standard Deviation*	*Min*	*Max*
Traffic	223.92	377.78	4	1821
Happiness	14.53	6.02	.0001	22.211
Poverty	21.74	5.87	11.8	39.3
Crime	866.18	377.42	359	1989
Cloudy	71.01	8.74	43	84.2
Population	1,243,976	1,694,304	262,396	8,491,079
Income	$30,066	$7,389.76	$1,4810	$51,727

Figure 3.1: Plot of Income vs. Happiness Score

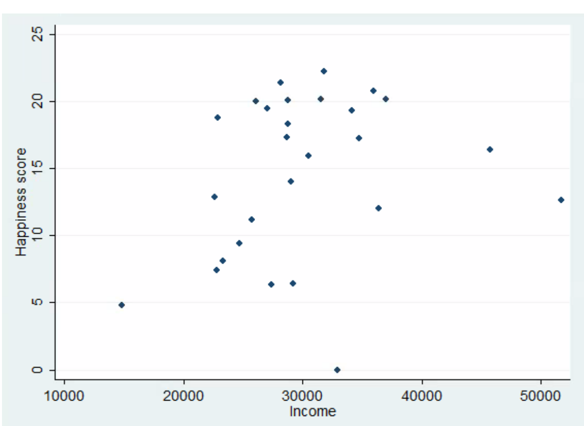


Figure 3.2: Plot of Cloudy vs. Happiness Score

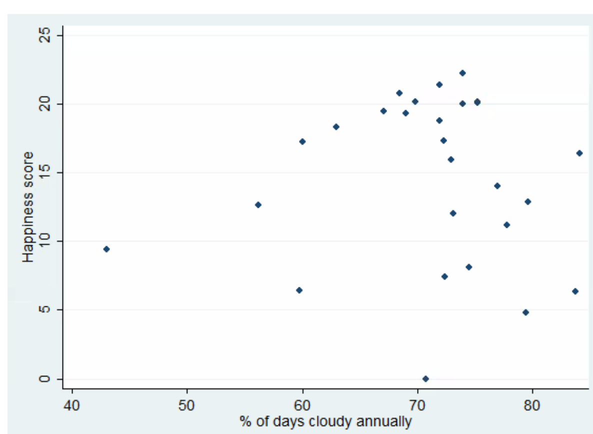


Figure 3.3: Plot of Crime vs. Poverty

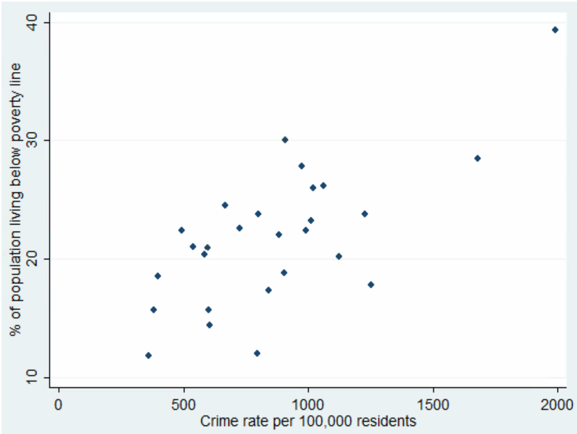
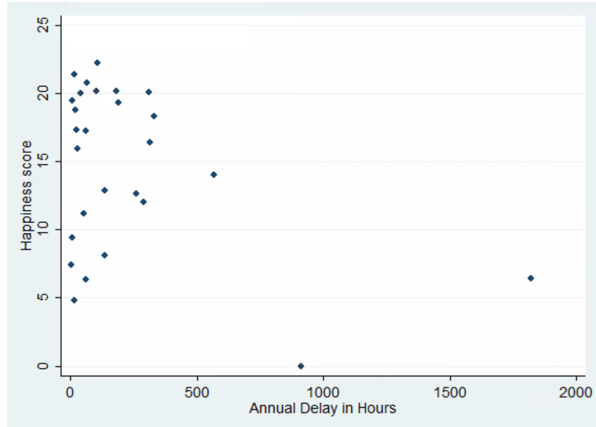


Figure 3.4: Plot of Delay vs. Happiness Score



IV. Results

Simple Linear Regression

Appendix A shows the results of a simple regression analysis where happiness was regressed against delay in each metropolitan area.

$$Happiness = -18.58 - .0045Traffic$$

Hypothesis:

$$H_0: \beta Traffic = 0$$

$$H_1: \beta Traffic \neq 0$$

It is seen that there is a slight negative correlation (-0.0045) between traffic and happiness, but this correlation is statistically insignificant because of the role other variables play in determining happiness. As delay increases, happiness of the population of the city is expected to go down slightly, however this coefficient is close to 0. For each additional hour spent in traffic per year, a person's happiness is expected to decline –0.0045. This is relatively small compared to the range of happiness values that we see in our data. This regression yields a weak R-Squared value of .158.

While this result does show that there is a statistically significant correlation between traffic and happiness, it does not show that this is a very large factor determining people's level of happiness. There are likely other variables that are more correlated with happiness in cities, such as weather, crime levels, and income. These variables contribution to happiness will be explored in the multiple regression analysis.

Multiple Regression

Appendix A shows the results of a multiple regression analysis.

$$Happiness = 25.83 - .0071Traffic - .386Poverty - .0015Crime$$

Hypothesis:

$H_0: \beta Traffic = 0$

$H_1: \beta Traffic \neq 0$

R-Squared: .3563

Adjusted R-Squared: .272

P-Value Traffic: .022

Since the number of observations is relatively small, the number of explanatory variables was also kept small. Contrary to other findings the number of cloudy or partly cloudy days was positively correlated with happiness. This is most likely due to the low number of observations. While income is also associated with happiness as positively correlated, a simple regression comparing happiness to income returned no statistical significance at 95% confidence level and a coefficient close to zero. This may be due to the small sample size. Additionally, this measure shows neither income distribution nor differences in costs of living across cities. In the multiple regression analysis poverty is negatively correlated with happiness but is not statistically significant. The same is true for the variable for crime rates. The addition of these two explanatory variables increased the R-squared value, as well as increasing the statistical significance and coefficient for traffic. Since none of these variables are perfectly collinear there is less chance the model exhibits bias.

Robustness

The explanatory variables population and income were tested for joint significance at 5%. These variables were found not to have joint significance, and were not used in the final model. When poverty and crime were tested for joint significance at 5%, they were found to be jointly significant.

Unrestricted Model:

$$Happiness = \beta_0 + \beta Traffic + \beta Poverty + \beta Crime + \beta Population + \beta Income$$

Restricted Model:

$$Happiness = \beta_0 + \beta Traffic + \beta Poverty + \beta Crime$$

$$H_0: \beta Income = 0, \beta Population = 0$$

$F_1 = 1.16$

critical value at 5% = 3.42

$F_1 < CV$

Fail to reject H_0

Unrestricted Model:

$$Happiness = \beta_0 + \beta Traffic + \beta Crime + \beta Poverty$$

Restricted Model:

$$Happiness = \beta_0 + \beta Traffic$$

$$H_0: \beta Poverty = 0, \beta Crime = 0$$

$F_2 = 3.51$

critical value at 5% = 3.47

$F_2 > CV$

Reject H_0

Regression Results

Dependent Variable: Happiness				
Independent Variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Traffic	-.0045	-.0067**	-.0071**	-.0023
	(.0031)	(.0026)	(.0029)	(.0038)
Population				-1.46E-6
				(8.17E-7)
Cloudy				.0775
				(.1229)
Crime			-.0015	-.0019
			(-.0071)	(.0040)
Poverty		-.4532**	-.3865	-.4067
		(.1688)	(.2480)	(.2565)
Intercept	18.58***	25.89***	25.83***	21.86***
	(1.385)	(3.87)	(3.94)	(8.30)
No. of obs.	27	27	27	27
R-square	0.078	0.35	0.356	0.45

*Significant at 10%, **5%, ***1%

V. Conclusions

The simple regression model we performed showed that traffic, as measured by total delay per year in hours by city, and happiness, as determined from self-reported survey data, do in fact share a statistically significant negative correlation. With data from the National Bureau of Economic Research on subjective well-being and "Worst Corridor" analysis on traffic delay, annually provided by INRIX, we were able to construct a sample size of 27 major metropolitan cities in the United States. The magnitude of this correlation is quite small relative to the range of possible happiness values, so it appears that traffic delay does not play a large role on perceived happiness.

The multiple regression analyses show that while traffic is a factor in determining people's happiness, it is not a major factor. This analysis provides evidence to support the claim that time spent in traffic only decreases happiness on a local time scale. Over a longer time-scale, it is possible that residents of high traffic cities adapt to the level of traffic and it no longer affects their happiness. A correlation exists between traffic and happiness, but this small correlation does not provide enough evidence that traffic has a large effect on a cities happiness levels. More research is needed to determine why short term differences in traffic measurably effect a person's happiness but variations across space and long durations of time do not.

The goal of this research was to provide further insight into the relationship between happiness and local levels of traffic. Data which encompasses more cities, including cities outside of the United States, would be ideal to provide greater insight into the specific effects of local traffic levels across cultures and national boundaries. Insight into the relative effects of other independent variables, such as crime, weather, and income per capita, will be deduced from the results of the multiple regression model and provide further insight into what other factors may be at play. If in fact traffic does not play a large role on the happiness of individuals, cities might take advantage of this insight to focus efforts on improving those factors which have greater effects on subjective well-being.

These results could be improved by adding additional cities to our dataset, especially those in Europe and Asia. The data we used was entirely comprised of US cities. This would seem like a good thing because it is one way to hold culture constant, however culture varies widely across the United States, so this supposed gain is actually nonexistent. Therefore, incorporating other cities into our data could be a good way to increase the robustness of our findings. If it is shown that European cities or Asian cities have higher correlations between traffic and happiness, our conclusion that happiness has a very small negative effect on traffic will have to be reevaluated. More data points, if they confirm the results from the United States, would increase the robustness of our results and allow certainty in the fact that average traffic does not have a strong effect on average happiness.

Appendix A: Stata Results

Simple Regression Results

Source	SS	df	MS			
				Number of obs	=	27
				F(1, 25)	=	4.69
Model	149.314684	1	149.314684	Prob > F	=	0.0401
Residual	795.985393	25	31.8394157	R-squared	=	0.1580
				Adj R-squared	=	0.1243
Total	945.300077	26	36.3576953	Root MSE	=	5.6426

Happiness	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Traffic	-.0063433	.0029292	-2.17	0.040	-.0123761	-.0003105
_cons	15.95483	1.268648	12.58	0.000	13.342	18.56766

Multiple Regression Results

Source	SS	df	MS			
				Number of obs	=	27
				F(3, 23)	=	4.24
Model	336.804061	3	112.26802	Prob > F	=	0.0159
Residual	608.496016	23	26.4563485	R-squared	=	0.3563
				Adj R-squared	=	0.2723
Total	945.300077	26	36.3576953	Root MSE	=	5.1436

Happiness	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Traffic	-.0071038	.002892	-2.46	0.022	-.0130863	-.0011213
Crime	-.001511	.0040501	-0.37	0.713	-.0098892	.0068672
Poverty	-.3864907	.2479804	-1.56	0.133	-.8994773	.1264959
_cons	25.83652	3.943061	6.55	0.000	17.67968	33.99337

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