SUPERSTITIONS, STREET TRAFFIC, AND SUBJECTIVE WELL-BEING*

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Abstract

Congestion plays a central role in urban and transportation economics. Existing estimates of congestion costs rely on stated or revealed preferences studies. We explore a complementary measure of congestion costs based on self-reported happiness. Exploiting quasi-random variation in daily congestion in Beijing that arises because of superstitions about the number four, we estimate a strong effect of daily congestion on self-reported happiness. When benchmarking this effect against the relationship between income and self-reported happiness we compute implied congestion costs that are several times larger than conventional estimates. Several factors, including the value of reliability and externalities on non-travelers, can reconcile our alternative estimates with the existing literature.

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Traffic congestion is a leading quality-of-life issue in most urban areas. Conventional estimates of traffic congestion costs aggregate the value of lost time, wasted fuel, and increased pollution and accidents due to congestion. In the United States (US) these estimates total $121 billion per year (Schrank, Lomax, and Eisele 2012), and the costs are particularly large in urban areas. For example, the Los Angeles metro area accrued $10.8 billion of congestion costs in 2011, representing 3% of income or 14% of housing costs. Congestion costs in other countries may be larger as a share of income; Creutzig and He (2009) estimate that congestion costs in Beijing represent 4% to 7% of municipal gross domestic product (GDP).

A critical element in determining congestion costs is motorists' value of time. Most estimates set the value of time at a fraction of the hourly wage (Liu et al. 2009), with the fraction typically determined by results from stated preferences (SP) studies or, less often, revealed preferences (RP) studies. Two recurring patterns in the literature are that SP estimates are often smaller than RP estimates and that motorists report a higher value of time in congested conditions than in free-flow conditions. These patterns suggest that the costs of traffic congestion are highly salient – motorists may not fully appreciate them until they directly experience them – and that driving in traffic entails some degree of psychic disutility. A related literature on travel reliability finds that motorists value reliability improvements – typically measured in standard deviations or interquantile differences of travel time – as much as they value reductions in mean travel time (Small 2012). These factors suggest that even reliable estimates of in-vehicle value of time are insufficient for calculating congestion costs.

In this work we estimate the effects of traffic congestion on subjective well-being in Beijing, China. In response to heavy congestion and pollution, Beijing restricts vehicle usage on the basis of license plate numbers. On any given weekday, private vehicles with plates ending in one of two digits may not drive within the 5th Ring Road from 7 am to 8 pm. As a result each vehicle is restricted one day per week. However, superstitions regarding the number four – which is homonymous with "death" in Chinese – dramatically reduce the proportion of vehicles with license plates ending in four. We thus expect, and find, large increases in traffic congestion on days on which plates ending in four are restricted. We combine data on congestion with data from the Chinese General Social Survey (CGSS) to estimate the effect of daily congestion levels – instrumented using a measure of the share of plates that are restricted each day – on self-reported happiness.

We use our estimates to apply an alternative method for valuing congestion costs. This method, based on self-reported levels of happiness, is novel to the transportation literature but has seen application in other contexts involving public goods or externalities. Our method compares the happiness effects of quasi-random daily changes in congestion levels to the happiness effects of additional income. If we treat happiness as a proxy for utility, this comparison reveals the utility-constant tradeoff between congestion and income. The method has both advantages and disadvantages vis-à-vis existing methods. It leverages quasi-random variation in congestion levels to estimate effects on subjective well-being. In this sense it avoids a frequent problem in RP studies, the potential confounding of travel-time differences with unobserved attributes. It measures subjective well-being for a random sample of the entire population, allowing inferences about the value of congestion costs for non-marginal individuals and individuals who are not travelers. It draws its outcome from a survey unrelated to transportation topics, avoiding SP-specific issues of framing bias, strategic response bias, or lack of information on the part of respondents.

There are natural disadvantages to the method as well. It treats subjective well-being as a proxy for utility. If it is a poor proxy – in particular if there is a systematic error term relating utility and subjective well-being – then our estimates will be biased. A related issue, endemic to many studies applying this method, is the lack of clearly exogenous wealth variation in our sample. Finally, to the extent that happiness is mean-reverting over the long run – i.e. individuals habituate to new life circumstances – comparisons between short-run changes in congestion and long-run changes in income may overstate the marginal rate of substitution between congestion and income. For these reasons we view our research design as complement to conventional approaches, and we note that shortcomings of the different approach are in general orthogonal to each other.

These caveats notwithstanding, we find that traffic congestion has a large negative effect on self-reported happiness. This "reduced form" result strongly suggests that congestion is a major determinant of quality-of-life, even in countries with moderate levels of GDP per capita. If we treat subjective well-being as a reasonable proxy for utility, our results imply that Beijing motorists' WTP to avoid an hour of congestion substantially exceeds the hourly wage rate. Although our WTP estimates are higher than those from the existing literature, several factors – including the value of reliability and potential external effects of congestion on non-travelers – can reconcile the two sets of estimates. Consistent with the large impact of congestion on quality-of-life, our estimates suggest significant potential welfare gains from congestion pricing.

I. Background

Congestion plays a central role in urban and transportation economics. The primary cost of congestion is lost time, and the value of travel time is a critical input in many transportation models. A rich literature – summarized in several meta-analyses and reviews – estimates this value across a variety of contexts (Zamparini and Reggiani 2007; Shires and De Jong 2009; Abrantes and Wardman 2011). Two types of studies, stated preferences and revealed preferences, populate this literature. SP studies present respondents with hypothetical scenarios and poll their WTP for specific goods or attributes. These studies offer the researcher precise control over the good or attribute in question and are helpful for valuing goods that are not traded on an open market. Nevertheless, they are subject to several types of biases: strategic bias, in which a respondent misreports to advance his own agenda; framing bias, in which a respondent's answer depends on how the surveyor frames the question; and information bias, in which respondents may not understand a scenario's details and have no incentive to figure them out.

In contrast to SP studies, RP studies examine individuals' actual choices. For example, an RP study might observe that commuters choose a transport mode that costs $1 more than an alternative but is 0.1 hours faster and conclude that commuters' value of time is at least $10 per hour. This methodology avoids biases specific to SP studies, but it can suffer from potential confounding of unobserved attributes with travel time differences. For example, if the faster transport mode is more comfortable, it is unclear how much of the observed WTP accrues from lower travel times and how much accrues from increased comfort. Alternatively, if the faster mode is less comfortable, the observed WTP will understate commuters' value of time. RP estimates are also challenging to generalize beyond individuals at the margin of choosing different modes.

Several patterns emerge in meta-analyses of the value of travel time. First, estimates from RP studies are consistently higher than estimates from SP studies. Shires and De Jong (2009), for example, analyze 1,299 estimates of the value of time and find that estimates based off SP methods are significantly smaller. Second, estimates of the value of time in congested conditions are significantly higher than estimates of the value of time in free-flow conditions. This finding suggests that motorists dislike the higher workload associated with driving in congested conditions or find these conditions frustrating in general. Finally, the elasticity of value of time with respect to GDP per capita is less than 1, suggesting that congestion may be a larger problem (as a share of income) in less developed countries.[1] However, there are very few estimates of value of travel time in low- or middle-income countries (Shires and De Jong, for example, report that their sample includes "only a few" middle-income countries and no low-income countries).

Given the limitations of many SP and RP studies, some of the cleanest estimates of the value of travel time come from studies of tolled highway express lanes. These studies leverage RP designs that are unlikely to be confounded by unobserved attributes, because the only difference between an express lane and a regular lane is the speed of traffic. Small, Winston, and Yan (2005) study the California SR91 express lanes and find an average value of time and average "value of reliability" (with reliability defined as the 90th minus 50th percentile of the travel-time distribution) each approximately equal to the hourly wage, or almost double the average of most value of time studies. They also find evidence of considerable heterogeneity in value of time and value of reliability. Devarasetty, Burris, and Shaw (2012) study toll lanes on Houston's I-10 and find a value of time savings of $51 per hour, or 1.5 times the hourly wage.[2] Bento, Roth, and Waxman (2014) analyze express lane choices in a model that considers "urgency," or the desire to jump a queue in order to meet a schedule constraint, and find that failing to consider schedule constraints generates an implied a value of time exceeding $100 per hour for 30% of express lane users.

The overall picture that emerges from this literature is that individuals value travel time but find congestion costly along dimensions beyond simple loss of time. They appear to have trouble anticipating the additional costs in hypothetical scenarios, suggesting a high degree of salience to the costs. Furthermore, costs are heterogeneous and grow less rapidly than per capita income. These patterns suggest an incomplete picture of total congestion costs in highly congested cities, particularly in developing or middle-income countries. In this context we view our happiness-based approach as providing complementary evidence on the costs of congestion in one of the world's largest cities.

Two other strands of literature relate to our study. First, a series of papers use subjective well-being measures to estimate tradeoffs in the provision of non-market goods in other contexts. These goods include inflation (Di Tella, MacCulloch, and Oswald 2001), airport noise (Van Praag and Baarsma 2005), terrorism (Frey, Luechinger, and Stutzer 2009), air pollution (Luechinger 2009), health (Finkelstein, Luttmer, and Notowidigdo 2013), and medical residency attributes (Benjamin et al. 2014). The paper closest to ours in this

[1] Abrantes and Wardman (2011) report a GDP elasticity of 0.9, with a tight confidence interval.

[2] Devarasetty et al. note that some of this value may represent value placed on increased reliability.

literature is Levinson (2012), which compares the happiness-constant rate of substitution between short-run changes in air pollution and higher incomes. A related literature examines the high-frequency time series relationship between happiness and daily activities. Of relevance to our study, Kahneman et al. (2004) find that, of 16 major daily activities (including work), individuals report the lowest positive affect levels during commuting. Over longer time horizons, Stutzer and Frey (2008) find that people with longer commutes systematically report lower subjective well-being. These findings suggest that most people find driving, particularly in congested conditions, to be a distasteful activity.

Finally, several papers study license plate restrictions in Beijing and other cities. Eskeland and Feyzioglu (1997) and Davis (2008) study a driving restriction scheme based on license plate digits in Mexico City and find no effect on gasoline demand and air quality measures respectively. Sun, Zheng, and Wang (2014) study the current Beijing license plate restrictions and find no relationship between PM_{10} and the number of plates restricted on a given day. Zhong (2015) uses a similar research design and finds evidence of modest effects of the plate restrictions on NO_2 levels and ambulance calls the next day. Viard and Fu (2015) study the introductions of the Beijing license plate restriction schemes and find significant declines in PM_{10} immediately following their introductions. While these different sets of results may seem contradictory, they do not measure the same policy effects. Viard and Fu estimate whether the license plate restrictions cause an immediate drop in pollution in the days following their introductions, while Sun et al. estimate whether the share of plates restricted affects pollution after the program has been running for a year or more. Zhong estimates the lagged effect on pollution after the program is in place. The Sun et al. result, which we confirm in our own data, suggests that air pollution is not a likely mechanism for any contemporaneous relationship we find between the share of vehicles restricted and self-reported happiness.

II. Data

Our study combines four data sets: a daily data set of congestion measures, an air quality data set, a weather data set, and the Chinese General Social Survey (CGSS). The congestion data consist of a transportation performance index (TPI) from the Beijing Municipal Commission of Transport (BMCT).[3] The TPI ranges from 0 to 10, with larger

[3] Our data are different from the publicly available data published online by the BMCT. The BMCT has modified the TPI formula over time to improve the index. The public data are not updated to include the modifications and thus are not consistently estimated with the same formula. We calculate our indices by feeding the raw data into the improved formula, so they are consistent over time.

values indicating worse traffic congestion. It is based on speeds observed across a large fleet of taxis using satellite navigation and wireless technology. The BMCT assigns weights to different roads and calculates the TPI as a weighted average across a large area.

Table 1 illustrates the relationship between the TPI and the needed travel time. Roughly, for TPI values between two and eight, a one-unit increase in the TPI corresponds to a 15% increase in travel time over a given distance relative to uncongested conditions. However, when the TPI reaches its upper limits, the marginal increase in travel time associated with a change in TPI can become very high. Our version of the TPI covers the area within the 5th Ring Road (i.e. the area subject to the license plate restriction) during the morning and evening peak hours (7 am to 9 am and 5 pm to 7 pm). We average the morning and evening indices to generate the daily TPI.

We have two indices for air quality. One is the daily average Air Pollution Index (API) for the entire Beijing area, published by the Beijing Municipal Environmental Monitoring Center.[4] The API counts PM_{10}, SO_2, and NO_2 as its main pollutants. Its value can range from 0 to 500. The other index is the $PM_{2.5}$ index published by the US Embassy in Beijing. The $PM_{2.5}$ monitor is located in the office space of the US Embassy, which is between the 3rd and 4th Ring Roads and is thus covered by the license plate restriction policy. The original data contain 24 hourly measurements per day, but to construct a daily index we take the average of the measurements between 7 am and 9 pm. This range of the hours limits us to times at which the license plate restriction policy is in effect and reduces the frequency of missing observations.

The weather variables come from the China Meteorological Data Sharing Service System. They include daily average rain, temperature, humidity, barometric pressure, hours of sunshine, maximum wind speed, and wind direction. Weather may affect driving behavior, air quality, and mood. To control for its influence on air quality, we interact wind speed with the four cardinal directions to get the wind speed from the north, east, south, and west. The upper panel of Table 2 presents the summary statistics for TPI, API, $PM_{2.5}$, and the weather variables from 2010 to 2012.

Our happiness data come from the Chinese General Social Survey conducted by Renmin University of China. The CGSS surveys a stratified random sample of households from the national population survey. The question on happiness reads, when translated to English, "Generally speaking, do you think whether you are happy?" Possible answers are: 1

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[4] In the appendix, we show that using the API for stations within the 5th Ring Road does not change our results. Therefore, for simplicity we use the city average API.

very unhappy; 2 unhappy; 3 in-between; 4 happy; and 5 very happy. Besides happiness, the survey also asks about basic demographics, including gender, age, household income, education, CPS (Communist Party of China) membership, marital status, household size, and home ownership. The CGSS also documents the date on which it was conducted. We use this date to merge the CGSS data with the daily data on TPI, API, $PM_{2.5}$ and weather.

The survey seeks to cover representative samples for the mainland area, and for our purpose we focus on the Beijing samples in 2010, 2011 and 2012. We restrict our sample to observations with non-missing information on happiness, gender, age, household income, and the survey date. This leads to a final sample of 1,195 observations – 75% of surveyed individuals – shown in Table 2. The lower panel of Table 2 reports summary statistics for the final sample. The average level of happiness is 3.9, and 65% of respondents report being "happy". The next most common answers are "very happy" (16%) and "in-between" (13%). Only 1% of the respondents reported being "very unhappy". Females account for 55% of the sample, and the average age is 49. The average annual household income per capita is 31,100 Yuan (approximately 5,000 US dollars), but the variance in income is larger than the mean. The average education is about 12 years (high school graduate), and household size ranges from one to nine with an average of 2.8 persons. Sixty percent of respondents own the house in which they live.

We examined two other surveys – a household survey conducted by the National Bureau of Statistics of China (NBS) and the China Family Panel Studies survey (CFPS) – to gauge the representativeness of the CGSS sample. When limiting the samples to Beijing residents, average household income is 29,400 Yuan in the NBS, 31,100 Yuan in the CGSS, and 33,900 Yuan in the CFPS. Average household size ranges from 2.7 to 2.8 in all three surveys. In general, our sample appears representative of the Beijing population.

III. Empirical Strategy

On any given weekday, the once-per-week driving restriction forbids cars with license plates ending in two different digits from driving in areas within the 5th Ring Road.[5] For convenience we refer to the last digit on a license plate as the "tail number." The once-per-week policy began on 11 October 2008, as an extension of traffic management policies introduced during the 2008 Summer Olympics. The weekday on which a given digit is restricted rotates every month from 11 October 2008 to 10 April 2009, and then every 13

[5] All cars may drive within the 5th Ring Road on weekends and holidays. Emergency vehicles, taxis, postal vehicles, and embassy vehicles are exempt from the license plate restrictions, but these vehicles comprise a small fraction of the total vehicle fleet.

weeks thereafter. For example, on Mondays the restricted digits are 1 and 6 between 11 October 11 2008 and 10 November 2008, 2 and 7 between 11 November 2008 and 10 December 2008, and 3 and 8 between 11 December 2008 and 10 January 2009. Table 3 lists the restricted digits on each weekday over time.

Table 4 shows the percentage of cars with license plates ending in each digit. The distribution is largely constant over the years, but the percentages differ remarkably across numbers. The digits – 1, 2, 3, 5, 7, and 0 – are each associated with about 10% of all cars, which is a "fair" share as there are ten digits. The digits 6, 8 and 9, which are traditionally considered lucky numbers, are each associated with 12% to 13% of cars. Most strikingly, the digit 4 accounts for only 1% to 3% of cars. In Chinese, four is homonymous with death, and people tend to avoid four in many aspects of the daily life, including floor number, door number, mobile phone number, and license plate number (as demonstrated here).[6]

The strong avoidance of the number four restricts only 14% of vehicles from driving on days when the tail numbers 4 and 9 are targeted, while 20% to 22% of cars are restricted on other dates. We define a variable, $tailpct_{dt}$, which equals the percentage of cars allowed on the road on date *t*. On weekends and holidays, the value is 100. On weekdays, $tailpct_{dt}$ varies from an average of 77.4 (when tail numbers 3 and 8 are restricted) to 85.9 (when tail numbers 4 and 9 are restricted).

Traffic congestion correlates with economic activity, weather, major events, transit disruptions, and any other factors that determine travel demand and supply. Since many of these factors may also affect individuals' moods, direct regressions of self-reported happiness on TPI are unlikely to estimate causal effects. The TPI is also an imperfect measure of any given individual's congestion experience and thus may be subject to measurement error. As an alternative research design we instrument for congestion, measured through the TPI, using variation in the percentage of cars allowed on the road, $tailpct_{dt}$. Since we control for day-of-week effects (thus eliminating variation caused by weekends and holidays), this strategy is similar to using an indicator for days on which the tail numbers 4 and 9 are restricted as the instrument, since those days are the main source of weekday variation in $tailpct_{dt}$. Indeed, using a simple binary instrument produces very similar results, but with slightly wider confidence intervals. Our main specifications take the form:

$$TPI_{dt} = \gamma_0 + \gamma_1 tailpct_{dt} + \boldsymbol{x_{idt}\gamma_2} + \boldsymbol{w_{dt}\gamma_3} + \boldsymbol{s_{dt}\gamma_4} + \boldsymbol{\delta_d} + \nu_{idt} \qquad (1)$$

[6] Shum, Sun, and Ye (2014) show that Chinese favor eight, and that apartments on the 8th floor of buildings are sold faster or at higher prices.

$$y_{idt} = \tau_0 + \tau_1 educ_{idt} + \boldsymbol{x_{idt}\tau_2} + \boldsymbol{w_{dt}\tau_3} + \boldsymbol{s_{dt}\tau_4} + \boldsymbol{\varphi_d} + u_{idt} \quad (2)$$

$$h_{idt} = \beta_0 + \beta_1 \widehat{TPI}_{dt} + \beta_2 \hat{y}_{idt} + \boldsymbol{x_{idt}\beta_3} + \boldsymbol{w_{dt}\beta_4} + \boldsymbol{s_{dt}\beta_5} + \boldsymbol{\theta_d} + \varepsilon_{idt} \quad (3)$$

We estimate both equations using observations on survey respondent *i* on day-of-week *d* on date *t*.[7] Equation (1) represents the first-stage relationship between the share of cars allowed on the road ($tailpct_{dt}$) and congestion (TPI). TPI varies at the daily level, and we assign each individual a TPI value, based on the TPI measurement on the day of his or her survey, in order to run the regression. Equation (2) represents the first-stage relationship between education ($educ_{dit}$) and income (y_{idt}). We instrument for income to address endogeneity concerns that we discuss below. Equation (3) represents the second-stage relationship between TPI and self-reported happiness (*h*); the coefficient of interest is β_1. β_1 should represent the local average treatment effect (LATE) of congestion on happiness, or the average effect for individuals for whom changing the instrument (share restricted) changes the value of the treatment (congestion). The instrument generates less variation in congestion for drivers with plates ending in 4 or 9 because they are restricted on the days with the worst traffic (though some will still have congestion exposure from taking a bus or taxi). Drivers with a high distaste for congestion thus may be more likely to accept plates ending in 4 or 9, and if so we expect the LATE to be smaller than the average treatment effect (ATE). This difference appears to be empirically modest however.[8]

The coefficient on predicted income, β_2, is also of interest in interpreting the magnitude of β_1. The vector $\boldsymbol{x_{idt}}$ includes predetermined individual level covariates: gender and a quadratic in age.[9] As long as survey sampling is random, these covariates will be uncorrelated with the survey day (and by extension the instrument) and are not necessary to reduce bias. However, they may be helpful in increasing precision. The vector $\boldsymbol{w_{dt}}$ contains weather and

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[7] Despite the appearance of both *i* and *t* indices, the data do not have a panel structure because we do not observe the same individual more than once. Rather, the data are effectively many repeated cross sections.

[8] If a substantial number of drivers choose plates to avoid high-congestion days, then we should see a disproportionate share of drivers choosing plates ending in 9, since 9 pairs with 4 and does not have negative connotations. However, the average share of plates ending in 9 is only modestly higher than the average share ending in any other digit besides 4 or 9 (12.1% versus 10.7%).

[9] We also have data on education, CPS (Communist Party of China) membership, marital status, household size, and home ownership. These covariates are uncorrelated with $tailpct_{dt}$, as we demonstrate in Table 5, and their inclusion or exclusion has no meaningful effect on our estimate of β_1. However, we do not include them as controls in Equation (3) because they are potentially endogenous to income and could thus bias our estimate of β_2.

air pollution variables discussed in Section II, and the vector $\boldsymbol{s_{dt}}$ contains month-of-sample indicators.[10] We also include the lag of *tailpct*$_{dt}$ in $\boldsymbol{w_{dt}}$ because other research has found some evidence of a relationship between current air pollution levels and lagged driving restrictions (Zhong 2015). The vectors $\boldsymbol{\delta_d}$, $\boldsymbol{\varphi_d}$, and $\boldsymbol{\theta_d}$ represent day-of-week effects, with an additional effect included for holidays.

Critical to our research design is the assumption that survey dates are random (more precisely, survey dates may be fixed, but the assignment of households to surveys dates should be random). If this is true, then after controlling for day-of-week effects household characteristics affecting happiness should be uncorrelated with the survey date and thus with the share of cars allowed on the road, *tailpct*$_{dt}$. This identifying assumption has the testable implication that household covariates should be uncorrelated with *tailpct*$_{dt}$. To test this hypothesis we estimate regressions of the form:

$$x_{kidt} = \pi_{k0} + \pi_{k1} tailpct_{dt} + \boldsymbol{\lambda_{kd}} + \xi_{kidt} \tag{4}$$

In these regressions, x_{kidt} represents household characteristic *k*, $\boldsymbol{\lambda_{kd}}$ are day-of-week effects for characteristic *k*, and other variables are as previously defined. If our research design is valid, then π_{k1} should not be significantly different than zero. Table 5 reports results from estimating Equation (4). There is no statistically or economically significant relationship between *tailpct*$_{dt}$ and any of our eight observable household characteristics, and the confidence intervals are generally tight enough to rule out coefficient values equal to more than a few percent of the dependent variable means. In separate regressions we also confirm a null relationship between weather and *tailpct*$_{dt}$ (see Appendix Table A1).

Equation (3) estimates the "reduced form" effect of traffic congestion on self-reported happiness, but β_1, the coefficient on congestion, does not have a direct economic interpretation. To interpret the magnitude of β_1 we compare it to the estimated relationship between per capita household income and self-reported happiness, represented by β_2. If self-reported happiness is a reasonable proxy for utility, then this comparison reveals the utility-constant tradeoff between congestion and income. Estimating β_2 requires an instrument for household income. Instrumenting in this context is important for two

[10] The survey does not occur continuously throughout each year, and start and end dates are not contiguous with the first or last day of the month. When generating the month-of-sample indicators we thus combine four observations in late July 2010 with the August 2010 observations, and four observations in late November 2011 with the December 2011 observations. Our results are not sensitive to these coding choices.

reasons. First, income – particularly permanent income – is measured with error.[11] This means that OLS estimates of the coefficient on income will be attenuated. Second, income may be confounded with unobserved determinants of happiness – for example, hours worked, psychological disposition, or workplace environment. These confounders could bias the OLS coefficient on income in either direction.[12]

Several previous happiness-based studies have used industry and occupation wage differentials as instruments for income (Luttmer 2005; Levinson 2012). We lack detailed data on industry and occupation of survey respondents, so we must instead use education ($educ_{dit}$) as an instrument for income. While instrumenting with education resolves some issues, including measurement error and the mechanical relationship between income and hours worked, there are important endogeneity concerns that it does not address. In particular, we may think that education has a direct effect on happiness independent of income, or that people who are predisposed to be happy are more or less likely to be highly educated. It is thus reassuring that our estimates of the elasticity of happiness with respect to income are of the same magnitude as those found in previous studies using alternative instruments for income.[13]

IV. Results

Table 6 reports our "first stage" estimates from Equation (1). These coefficients reveal the effect of the percentage of cars allowed on the road on traffic congestion and air pollution. The first column of Table 6 estimates the effect on congestion (TPI) with day-of-week effects, month-of-sample effects, and weather variables as controls. The coefficient is highly significant (t = 5.3) and implies that a 10 percentage point increase in the share of cars allowed on the road increases the congestion index by 1.54 units, or 29% of the mean. In terms of travel delay relative to uncongested conditions, a 10 percentage point increase in the share of cars allowed on the road increases travel delay by approximately 32%.[14] The second column adds controls for respondent characteristics. The coefficient is virtually unchanged

[11] A classic series of papers on intergenerational income mobility make this point explicitly (Solon 1992; Zimmerman 1992; Mazumder 2005).

[12] One source of bias in the OLS estimates is that some variation in wages reflects compensating differentials for unpleasant occupations. That variation induces a negative bias in the OLS estimates that should not be present with the education instrument.

[13] For example, Levinson (2012) estimates that a one-unit increase in log income is associated with a 6% increase in average self-reported happiness. We estimate that a one-unit increase in log income is associated with a 7% increase in average self-reported happiness.

[14] The average TPI level in our analytic sample is 5.4, which corresponds to 0.71 minutes of travel delay relative to the uncongested condition (see Table 1). A 1.5 unit increase in TPI corresponds to an additional 0.23 minutes of travel delay, or a 32% increase.

and remains highly significant ($t = 5.3$). The third column expands the sample to include days on which the CGSS is not conducted; the unit of observation changes from the individual-by-day to the day. This increases the number of days in the sample by almost a factor of 10 (note, however, that N does not change by a factor of 10 because the unit of observation has changed). While we cannot use these additional days to estimate happiness regressions, they are useful in increasing the precision of our first-stage estimates. The regression coefficient is close to the estimate in Column (1), but the t-statistic increases to $t = 16.1$.

The relationship between the percentage of cars restricted and travel delay is approximately what we might predict from theory. Standard congestion models specify driving delay as a power function of traffic volume, with an exponent – and thus an elasticity of delay with respect to volume – in the range of 3 to 4 (Parry and Small 2009). In comparison we find an implied elasticity of travel delay with respect to share of cars allowed of 2.6.[15] This is slightly lower than previous estimates, but there are two reasons to expect this. First, some vehicles, such as taxis, emergency vehicles, and postal vehicles, are exempt from the restrictions. Second, there may be imperfect compliance with the restrictions.[16] Both of these factors imply that the proportionate increase in traffic volume is less than the proportionate increase in the share of cars allowed.

The last six columns of Table 6 present results from versions of Equation (1) in which we replace the TPI with air quality measures. Columns (4) through (6) report results for the air pollution index, while Columns (7) through (9) report results for $PM_{2.5}$. In all cases there is a small and statistically insignificant relationship between air quality and the share of cars allowed on the road. The estimates in Columns (6) and (9), which include days on which the CGSS does not occur, are relatively precise. For example, we can reject the hypothesis that a 10 percentage point increase in the share of cars allowed raises the API by more than 7.3% or $PM_{2.5}$ by more than 6.4%. While these results may seem surprising, they are consistent with the findings in Sun et al. (2014), and it is notable that only 17% of $PM_{2.5}$ concentrations in Beijing come from vehicle exhaust (Yu et al. 2013). A modest change in vehicle volumes is thus unlikely to generate any detectable change in air pollution. These results suggest that air

[15] Approximately 80% of cars are allowed to drive on any given weekday, so a 10 percentage point increase in cars allowed represents a 12.5% increase from baseline levels. Travel delay increases 32%, so the implied elasticity is $0.32/0.125 \approx 2.6$.

[16] Wang, Xu, and Qin (2014) estimate that up to 48% of regulated vehicles on any given day may be driven "illegally" within the 5th Ring Road between 7 am and 8 pm.

pollution is not a likely mechanism for any effect of the share of vehicles allowed on happiness.

Table 7 reports results of estimating Equation (3), two stage least squares (2SLS) regressions of happiness on congestion and income. For comparison purposes, Column (1) reports results from an OLS regression of happiness on the TPI and log household income while controlling for day-of-week effects, month-of-sample effects, weather, and respondent age and gender. There is no significant relationship between congestion and happiness, and the 95% confidence interval rules out coefficient larger than –0.043. There is considerable variation in daily congestion, as measured by the TPI, even after controlling for day-of-week, month-of-sample, and weather effects, and only 10% of this variation comes from our instrument. We do not have strong expectations on whether the underlying factors causing fluctuations in traffic volumes, such as economic activity and major events, are likely to have positive or negative relationships with happiness, and thus we do not have an *ex ante* expectation about the direction of bias in the OLS coefficient. The coefficient on log household income, 0.132, is highly significant (t = 4.1) and implies an elasticity of happiness with respect to income of 0.03. We expect the OLS coefficient on income to be attenuated due to measurement error concerns that are well-established in the labor literature (Stevenson and Wolfers 2008).

Column (2) reports 2SLS estimates from regressing happiness on the TPI (using *tailpct* as the instrument) and day-of-week effects, month-of-sample effects, and weather. A one-unit increase in the TPI, which corresponds to about a 15% increase in travel delay, reduces self-reported happiness by 0.169 units (t = 2.7), or approximately 0.2 standard deviations. Column (3) adds controls for respondent gender and age; the point estimates and statistical significance on the TPI coefficient are virtually unchanged. Column (4) regresses happiness on log household income (instrumented for using years of education), controlling for day-of-week effects, month-of-sample effects, weather, and respondent gender and age. An approximate doubling of household income increases self-reported happiness by 0.268 units (t = 3.3), or approximately 0.4 standard deviations. Column (5) includes both congestion and household income in the 2SLS regression simultaneously. Since our two instruments – share of cars allowed on the road and respondent education – are orthogonal to each other, we do not expect joint estimation of the two coefficients of interest to yield significantly different estimates, and the jointly estimated coefficients are similar to the estimates in Columns (3) and (4) and retain the same significance levels. Column (6) limits the sample to weekdays, since this is when all of the usable variation in our instrument occurs. The coefficient declines slightly in magnitude but remains statistically significant. The last column further limits the sample to only 2010 and 2011; in 2012 the CGSS occurred during a brief period during which the weekday on which each digit was restricted did not rotate. The coefficient and standard error both increase, but the estimate remains statistically significant.

Table 8 reports the effects of congestion and income on the probability of reporting each of the five possible happiness categories. In each column *j*, we replace the dependent variable with an indicator for whether an individual reports a happiness level of *j*. Although precision is limited, we see that congestion significantly reduces the share of people that report being "very happy" and significantly increases the share of people that report being "very unhappy". The latter coefficient is small in raw percentage points, but it is more than double the average share that reports being "very unhappy". Additional household income decreases the share of people that report being "unhappy" – with a significant point estimate that is double the average share that reports being "unhappy" – and increases the share of people that report being "very happy".

The two stage least squares estimator consistently estimates the "average causal response" of happiness to congestion even when the dependent variable is categorical (Angrist and Imbens 1995). Nevertheless, as a robustness check we estimate an ordered probit model as well. The ordered probit is a better fit for our data than alternatives like the multinomial logit because the happiness variable's categories have a clear ordering. To address the endogeneity of congestion and household income, we apply a Rivers-Vuong control function approach using our two instruments (share of cars allowed on the road and respondent education). Specifically, we estimate ordered probit analogs of Equation (3), but instead of including $\widehat{TPI}_{dt}$ and $\hat{y}_{idt}$ as regressors, we include TPI_{dt} and y_{idt} as regressors and control for their respective first-stage residuals, $\hat{v}_{idt}$ and $\hat{u}_{idt}$.[17]

Table 9 reports results from the ordered probit control function model. The point estimates are not directly comparable to the 2SLS results in Table 7 because the ordered probit index coefficients do not represent marginal effects. Nevertheless, the results are qualitatively similar; congestion has a significant negative effect on happiness, and income has a significant positive effect. The key quantitative comparison between the tables is the ratio of the TPI and income coefficients, as this ratio determines the marginal rate of

[17] Following Rivers and Vuong (1988) we rescale the raw ordered probit coefficients on TPI_{dt} and y_{idt} by $\left(1+\hat{\theta}_v^2\hat{\sigma}_v^2\right)^{-0.5}$ and $\left(1+\hat{\theta}_u^2\hat{\sigma}_u^2\right)^{-0.5}$ respectively, where $\hat{\theta}_v$ ($\hat{\theta}_u$) is the coefficient on $\hat{v}_{idt}$ ($\hat{u}_{idt}$) and $\hat{\sigma}_v$ ($\hat{\sigma}_u$) is the root mean square error from the first stage regression for TPI (income). We calculate standard errors using a cluster bootstrap clustered on date.

substitution between income and travel delays. The ratio is –0.59 in the 2SLS regressions (Columns (3) and (4) of Table 7) and –0.60 in the ordered probit regressions (Columns (2) and (3) of Table 9). Our conclusions thus appear robust to alternative nonlinear estimation methods.

V. Discussion

Our preferred estimates for the effects of TPI and log household income are –0.159 and 0.268 respectively (Columns (3) and (4) of Table 7). These estimates leverage the full sample of available CGSS observations, include the same controls, and are more precise than the joint estimates in Column (5) of Table 7. One possible explanation for the TPI coefficient is that it represents changes in activities due to plate restrictions rather than changes in congestion. Economic theory predicts that, conditional on congestion levels, a lower number of plate restrictions should increase happiness, so the fact that fewer plates are restricted on 4/9 restriction days cannot in general explain our findings. Nevertheless, people may be more likely to work on days when fewer plates are restricted, and work may have a negative effect on happiness. Back-of-the-envelope calculations, however, suggest that this explanation – which represents a violation of the exclusion restriction – is implausible. A one unit change in the TPI corresponds to an 8% increase in vehicles allowed to drive. The change in labor supply would be much less than 8% since many workers do not drive or could find alternate transportation arrangements. Even a 5% increase in labor supply, however, would require the effect of working on happiness to be on the order of –3.2.[18] This represents a change of over four standard deviations in happiness and is implausibly large.

The implied tradeoff between congestion and household income is large. The ratio of the TPI and log household income coefficients implies that respondents are willing to forfeit approximately $6 for a one standard deviation improvement in congestion levels for a single day. While this value is small compared to results from developed countries – Levinson (2012) finds, for example, that people are willing to sacrifice $35 for a one standard deviation improvement in air quality for one day – it represents approximately 40% of mean daily per capita household income in our sample. The estimate seems plausible when interpreting the happiness index as a quality-of-life measure, but can we reconcile it with existing estimates of WTP to avoid travel delays?

[18] The estimated effect of TPI on happiness is –0.16. If this effect is running through a change in labor supply, and labor supply increases by only 5%, then the average effect of working on happiness for those whose labor supply changes must be –0.16/0.05 = –3.2. This calculation is actually a lower bound since it ignores the fact that some CGSS respondents are in household where no one works (e.g. they may be retirees).

The simplest comparison is to consider the change in congestion that would offset the happiness effect of a 10 percent increase in household income. A 10 percent increase in income raises happiness by 0.027 units, and offsetting this increase requires a rise in the TPI of 0.2 units, or about 4% of the average travel delay. The average per capita household income in our sample is approximately 5,000 US dollars, suggesting that individuals are willing to pay approximately 34 US cents per day to decrease travel delay by 1%.[19] The implied happiness-constant elasticity of substitution between income and travel delays is 2.5.

An elasticity of substitution of 2.5 is high. Our happiness measure, however, may incorporate a variety of effects, some of which traditional congestion cost measures may miss. These include potential increases in accidents and disutility arising from schedule changes and trip cancellations. Furthermore, the congestion effects that we measure are not necessarily limited to travelers. They may include schedule disruption and dissatisfaction among family, friends, or colleagues of travelers who arrive late or in an unpleasant mood. We refer to these effects as non-traveler externalities (note that an individual's status as a traveler is dynamic; an individual who is a traveler at one time of day is likely a non-traveler at other times of day). In contrast, our happiness measure will not capture effects that individuals do not immediately internalize. These include changes in workplace productivity or longer-term medical costs arising from accidents, stress, or pollution.

To tie our findings to the existing literature on congestion costs we consider the implied value of travel time and reliability relative to the wage. To do this we note that approximately half of our CGSS respondents report working in the past week and that, among those that do work, the average hours worked per week is approximately 40. A 10% increase in income is, on the margin, equivalent to granting the average individual an additional 1.8 hours of leisure per week, or 0.25 hours per day. The hours lost to a 4% change in travel delay – the happiness-constant equivalent of a 10% change in income – depend on the average level of travel delay in Beijing. Travel delay accrues to drivers, bus riders, and taxi passengers. Creutzig and He (2009) estimate an average weekday per capita delay – across cars and buses – of 0.74 hours in 2005. Vehicle registrations approximately doubled from 2005 to 2011, and bus ridership grew 12%. A conservative estimate for per capita weekday travel delay circa 2011 is 1.22 hours, 4% of which is 0.05 hours.[20] This implies that individuals are willing to

[19] At 365 days per year, 10% of average per capita household income equates to $1.37 per day. Since 10% of average income has an equivalent effect to a 4% change in travel delay, WTP to decrease travel delay by 1% should be approximately 34 US cents (i.e. one-quarter of $1.37).

[20] Creutzig and He report 1.81 billion hours of total delay, with 0.81 billion hours of annual auto delay (0.64 billion hours for drivers and 0.17 billion hours for passengers) and 1 billion hours of annual bus passenger

trade off 0.25 hours of leisure for 0.05 hours of travel delay, or a ratio of approximately 5 to 1.

A value of travel delay equivalent to five times the wage is considerably higher than previous estimates of value of travel time from SP studies. Zamparini and Reggiani (2007), for example, report an average value of travel time savings equal to 83% of the wage rate across 90 studies, and previous studies in Beijing have valued travel time savings at approximately 140% to 170% of the average wage (Beijing Transportation Research Center 2005). Nevertheless, several factors combined can reconcile our results with the existing literature on value of travel time. First, the elasticity of value of time (VOT) with respect to income appears to be less than one; Zamparini and Reggiani find an elasticity with respect to income of 0.7. Since incomes in Beijing are lower than incomes in the US and Europe, we should expect the ratio of the VOT to the hourly wage to be up to 50% higher in Beijing.[21] Second, as noted above, our outcome measures the impact of delays on travelers and non-travelers. If delays affect non-travelers as well as travelers – i.e. if schedule disruptions generate externalities on non-travelers – then our estimated effects should be larger than simple value of travel time savings would suggest. Third, drivers display a higher VOT in congested conditions than in free-flow conditions; Abrantes and Wardman (2011) report that time in congested conditions is valued 54% more than time in free flow conditions. Finally, our congestion instrument captures variation in both travel time and reliability. Since the value of reliability (VOR) is often estimated to be as high as the VOT, we may expect our estimates to be up to twice as high as the value of time alone.[22]

A simple model of scheduling costs is helpful in understanding how VOT and VOR factor into our results. Vickrey (1969) postulates a model of scheduling costs involving "alpha-beta-gamma" preferences, with the parameters referring to the per minute cost of

delay. Across 9.8 million residents within the 6th Ring this implies 185 hours annually per capita or 0.74 hours per capita per weekday. Total vehicle registrations had increased 93% by 2011 and private automobile registrations had increased 177%; since it is unclear which measure is preferable we take the geometric mean of these two figures, or 131%. Increasing the auto delay by 131% to 1.87 billion hours and increasing the bus delay by 12% to 1.12 billion hours generates a per capita weekday delay of (1.87 + 1.12)/(0.0098*250) = 1.22 hours per capita per weekday. This estimate is conservative in that it assumes traffic management policies have been sufficient to keep traffic speeds from declining further since 2005.

[21] In 2011 the average US wage was approximately four times higher than the average Beijing wage. An elasticity of 0.7 implies that US VOT should be $4^{0.7} = 2.64$ times higher than the Beijing VOT. Thus the ratio of VOT to wage should be 1/(2.64/4) = 1.52 times higher in Beijing than in the US.

[22] Of course, there are also reasons why *ex ante* one might expect that the VOT could be lower than the wage. One possibility is if individuals get more disutility from work than they do from being stuck in traffic (though time diary data that we cite in Section I suggests that commuting is the most distasteful activity that people regularly engage in). Another possibility is if individuals have limited flexibility in work hours and thus are not working up to the points at which their marginal values of time equal their wage rates.

travel time (α), the per minute cost being early (β), and the per minute cost of being late (γ). The conventional choice of parameters is $\gamma = 2\alpha = 4\beta$, implying that the cost of being late is double the cost of travel time (Small 2012). This model generates a sizeable VOR because, when faced with unreliability, travelers must either bear the risk of being late or pad their schedules and incur the (expected) cost of being early. In our study, if many commuters are not aware that days on which the digit 4 is banned experience higher congestion, or cannot precisely forecast how much delays increase on these days, then much of the additional travel delay will materialize as lateness – which individuals value at double the VOT. In some cases, even doubling the VOT may not fully capture the cost of being late (Bento et al. 2014).

Back-of-the-envelope calculations suggest that these factors can plausibly explain the high costs of congestion that we find. Recall that our results imply that individuals value additional delay at 500% of the wage. Assume that the average VOT in the US or Europe is 80% of the wage. Given the lower per capita GDP in Beijing we might expect the Beijing-specific VOT to be 120% of the wage and the cost of being late to be 240% of the wage. A 50% penalty to VOT in congested conditions raises the average travelers' delay cost to 300% of the wage, implying that external costs should be approximately two-thirds as large as travelers' costs in order to fully explain our results.[23] Note that an individual's status as a traveler is not fixed over time; travelers during one part of the day may be non-travelers experiencing external costs during other parts of the day.

Our results demonstrate a clear negative effect of congestion on quality-of-life. The implied tradeoff between travel delay and income is large but not inconsistent with a range of estimates from the existing literature on valuing travel time. Nevertheless, several caveats are worth noting. First, to the degree that self-reported happiness is a poor proxy for utility, comparisons of the coefficients on congestion and income will not reveal the utility-constant tradeoff between the two goods. Second, since we do not have an ideal instrument for income, the coefficient on income may not represent a causal effect. Third, although our research design allows us to theoretically measure effects for non-marginal travelers and non-travelers, it does not allow us to disaggregate these effects into their individual components.

Finally, our estimates compare the effects of short-term, potentially unanticipated changes in congestion to the effects of long-term differences in income. In both cases the

[23] We assume that the 50% penalty in congested conditions applies to the VOT (120% of wage) rather than the value of being late. Thus the penalty is 0.5*1.2 = 60% of the wage. If external costs are two-third of travelers' costs, then they will add an additional 0.67*3 = 200% of the wage, and total costs will be 500% of the wage.

time scale of the variation that we leverage may affect our coefficient estimates. If travelers do not anticipate the increased congestion on days on which tail number four is banned, they will not adjust their departures in anticipation of the increased congestion. In that sense our estimates represent an upper bound on the effects of an anticipated increase in congestion (as opposed to unanticipated fluctuations in congestion). Likewise, the coefficient on income may not represent the effect of a sudden change in income. In particular, if individuals "adapt" to higher levels of income over time, then the effect of a recent change in income on happiness may be larger than the effects of long-term cross-sectional differences in income on happiness (Oswald and Powdthavee 2008; Kimball, Nunn, and Silverman 2015).

VI. Conclusion

Although our happiness-based estimates come with significant caveats, they represent a complementary tool to traditional SP and RP studies for valuing congestion costs. Importantly, their shortcomings are generally orthogonal to the issues that affect most SP and RP studies. Thus, to the degree that we can reconcile our estimates with the existing literature, it should make us more confident in both sets of estimates. Unlike most conventional approaches, our methodology also allows us to include costs of non-marginal travelers and non-travelers.

Our estimates have clear policy implications. First, congestion strongly impacts quality-of-life, as represented by self-reported happiness. Interpreting this "reduced form" result requires fewer caveats than our other results and underscores the potential social gains to congestion pricing. Second, the implied happiness-constant tradeoff between income and congestion is quite large. When interpreted as a fraction of the wage, it suggests that existing estimates of congestion costs may be lower bounds. Future research might explore the degrees to which this result accrues through different channels, such as high penalties to failing to meet scheduling constraints or external costs imposed on non-travelers users.

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Table 1: Interpreting the Traffic Performance Index (TPI)

Index	Description	Travel Time
0 – 2	Smooth	1 minute
2 – 4	Basically smooth	1.2-1.5 minutes
4 – 6	Slightly congested	1.5-1.8 minutes
6 – 8	Moderately congested	1.8-2.1 minutes
8 – 10	Seriously congested	> 2.1 minutes

Notes: Travel time corresponds to the amount of time to travel a given distance. The relevant distance varies with the free-flow speed of the road.

Table 2: Summary Statistics

Variable	Obs	Mean	Std Dev	Min	Max
Panel A: Traffic, weather, and pollutant data (2010-2012)					
AM TPI	1,073	3.70	2.03	0.8	9.4
PM TPI	1,080	5.21	2.11	0	10
Daily TPI	1,070	4.48	1.85	1	9.7
API	1,091	81.8	45.1	15	500
PM2.5	1,053	93.7	76.1	2.9	473.7
Rain (0.1mm)	1,096	18.0	77.9	0	829
Temperature (0.1℃)	1,096	130	117	-125	345
Humidity (1%)	1,096	50.4	20.3	9	97
Barometric pressure (0.1hPa)	1,096	10,125	101.7	9,904	10,373
Sunshine (0.1h)	1,096	66.8	40.6	0	138
Max wind speed (0.1m/s)	1,096	49.5	18.0	17	120
Panel B: Household and individual data from the CGSS					
Happiness	1,195	3.92	0.74	1	5
very unhappy, = 1		1%			
unhappy, = 2		5%			
in-between, = 3		13%			
happy, = 4		65%			
very happy, = 5		17%			
Male	1,195	0.45	0.50	0	1
Age	1,195	48.8	16.2	17	91
Income per capita (1000yuan)	1,195	31.1	34.3	0.3	500
Education (years)	1,194	11.92	3.61	0	18
CPC membership	1,191	0.23	0.42	0	1
Married	1,195	0.77	0.42	0	1
Household size	1,195	2.80	1.21	1	9
House ownership	1,192	0.60	0.49	0	1

Table 3: Tail Number Restrictions Over Time

Start Date	End Date	Monday	Tuesday	Wednesday	Thursday	Friday
10/11/2008	11/10/2008	1/6	2/7	3/8	4/9	5/0
11/11/2008	12/10/2008	2/7	3/8	4/9	5/0	1/6
12/11/2008	1/10/2009	3/8	4/9	5/0	1/6	2/7
1/11/2009	2/10/2009	4/9	5/0	1/6	2/7	3/8
2/11/2009	3/10/2009	5/0	1/6	2/7	3/8	4/9
3/11/2009	4/10/2009	1/6	2/7	3/8	4/9	5/0
4/11/2009	7/10/2009	5/0	1/6	2/7	3/8	4/9
7/11/2009	10/9/2009	4/9	5/0	1/6	2/7	3/8
10/10/2009	1/8/2010	3/8	4/9	5/0	1/6	2/7
1/9/2010	4/10/2010	2/7	3/8	4/9	5/0	1/6
4/11/2010	7/10/2010	1/6	2/7	3/8	4/9	5/0
7/11/2010	10/9/2010	5/0	1/6	2/7	3/8	4/9
10/10/2010	1/8/2011	4/9	5/0	1/6	2/7	3/8
1/9/2011	4/10/2011	3/8	4/9	5/0	1/6	2/7
4/11/2011	7/9/2011	2/7	3/8	4/9	5/0	1/6
7/10/2011	10/8/2011	1/6	2/7	3/8	4/9	5/0
10/9/2011	1/7/2012	5/0	1/6	2/7	3/8	4/9
1/8/2012	4/10/2012	4/9	5/0	1/6	2/7	3/8
4/11/2012	7/10/2012	3/8	4/9	5/0	1/6	2/7
7/11/2012	10/9/2012	2/7	3/8	4/9	5/0	1/6
10/10/2012	1/8/2013	1/6	2/7	3/8	4/9	5/0
1/9/2013	4/7/2013	5/0	1/6	2/7	3/8	4/9
4/8/2013	7/6/2013	4/9	5/0	1/6	2/7	3/8
7/7/2013	10/5/2013	3/8	4/9	5/0	1/6	2/7
10/6/2013	1/4/2014	2/7	3/8	4/9	5/0	1/6
1/5/2014	4/11/2014	1/6	2/7	3/8	4/9	5/0

Notes: Each column lists the tail numbers restricted on that column's day over different time periods.

Table 4: Distribution of Tail Numbers by Year

	Percent of cars with tail number in:			
Tail number	2009	2010	2011	2012
1	10.0	9.9	9.9	9.9
2	10.2	9.9	9.9	9.9
3	9.9	9.7	9.6	9.6
4	2.8	2.3	2.2	1.9
5	10.4	10.4	10.5	10.6
6	11.7	12.1	12.3	12.3
7	10.1	10.1	10.2	10.3
8	12.7	13.0	12.9	12.9
9	11.6	12.1	12.2	12.3
0	10.6	10.5	10.5	10.5
1 or 6	21.7	22.0	22.1	22.2
2 or 7	20.3	20.1	20.0	20.1
3 or 8	22.6	22.6	22.5	22.4
4 or 9	14.4	14.4	14.4	14.1
5 or 0	21.0	20.9	21.0	21.1

Notes: In each panel, each column sums to 100 (up to rounding error).

Table 5: Relationship Between Share Cars Allowed and Household Characteristics

Dependent Variable:	Male	Age	HH income	Education	CPC	Married	HH size	Owner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Percent cars allowed	0.004	-0.07	0.65	-0.03	0.000	0.002	0.030	-0.011
(*tailpct*)	(0.007)	(0.30)	(0.44)	(0.04)	(0.008)	(0.007)	(0.021)	(0.007)
Dependent variable m	0.453	48.77	31.09	11.92	0.226	0.772	2.804	0.604
N	1,195	1,195	1,195	1,194	1,191	1,195	1,195	1,192

Notes: Each column reports results from a regression of the dependent variable on the percentage of cars allowed to drive on a given day and day-of-week indicators. The level of observation is an individual survey respondent. Parentheses contain standard errors clustered by date. Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.01$.

Table 6: First-Stage Relationships Between Share Cars Allowed, Congestion, and Air Pollution

Dependent Variable:	TPI (congestion)			API (air pollution)			$PM_{2.5}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Percent cars allowed	0.154***	0.155***	0.145***	0.49	0.47	0.03	0.10	0.07	-0.25
(*tailpct*)	(0.029)	(0.029)	(0.009)	(0.95)	(0.94)	(0.35)	(2.12)	(2.11)	(0.52)
CGSS sample days only	Y	Y		Y	Y		Y	Y	
Male		-0.002			0.21			-0.18	
		(0.061)			(1.67)			(3.08)	
Age (decades)		-0.018			4.80			8.81	
		(0.094)			(2.79)			(5.04)	
Age^2 (decades)		0.003			-0.51			-0.95	
		(0.010)			(0.28)			(0.52)	
Dependent variable mean	5.376	5.376	4.505	77.14	77.14	83.05	111.18	111.18	95.44
N	1,195	1,195	1,427	1,195	1,195	1,469	1,109	1,109	1,713

Notes: Each column reports results from a regression of the dependent variable on the percentage of cars allowed to drive on a given day, day-of-week and month-of-sample indicators, lagged percentage of cars allowed to drive, and weather variables. Columns (1) through (3) also include air pollution controls. The level of observation is an individual survey respondent except in Columns (3), (6), and (9), in which it is a day. Parentheses contain standard errors clustered by date. Significance: * p<0.05; ** p<0.01; *** p<0.001.

Table 7: OLS and 2SLS Relationships Between Happiness, Congestion, and Income

Dependent Variable:	Self-reported Happiness						
Estimator:	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(6)	(7)	(8)	(9)
TPI (congestion)	-0.007	-0.169**	-0.159**		-0.180**	-0.158**	-0.208*
	(0.018)	(0.062)	(0.061)		(0.065)	(0.060)	(0.083)
Log HH income	0.132***			0.268***	0.259**		
	(0.031)			(0.081)	(0.087)		
Male	-0.096*		-0.082*	-0.108**	-0.106*	-0.041	0.007
	(0.040)		(0.041)	(0.042)	(0.046)	(0.050)	(0.064)
Age (decades)	-0.210**		-0.244**	-0.174*	-0.178*	-0.298***	-0.187
	(0.077)		(0.077)	(0.075)	(0.073)	(0.089)	(0.108)
Age^2 (decades)	0.025**		0.028***	0.022**	0.023**	0.033***	0.021
	(0.008)		(0.008)	(0.008)	(0.007)	(0.009)	(0.011)
Drop weekends/holidays						Y	Y
Drop 2012							Y
Dependent variable mean	3.92	3.92	3.92	3.92	3.92	3.92	3.97
N	1,195	1,195	1,195	1,194	1,194	848	586

Notes: Each column reports results from an OLS or 2SLS regression of the dependent variable on the daily TPI (using the percentage of cars allowed to drive on a given day as the instrument) and/or log household income (using a respondent's years of education as the instrument). All regressions include day-of-week and month-of-sample indicators, lagged percentage of cars allowed to drive, and weather and air pollution variables. The level of observation is an individual survey respondent. Parentheses contain standard errors clustered by date. Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Table 8: 2SLS Relationships Between Happiness Categories, Congestion, and Income

	Self-reported happiness level is:				
Dependent Variable:	Very unhappy	Unhappy	In-between	Happy	Very happy
	(1)	(2)	(3)	(4)	(5)
TPI (congestion)	0.020*	0.009	0.024	0.023	-0.077*
	(0.010)	(0.018)	(0.026)	(0.042)	(0.034)
Log HH income	-0.011	-0.056*	-0.026	0.007	0.087
	(0.009)	(0.022)	(0.036)	(0.054)	(0.047)
Dependent variable mean	0.008	0.047	0.126	0.653	0.165
N	1,194	1,194	1,194	1,194	1,194

Notes: Each column reports results from a 2SLS regression of the dependent variable on the daily TPI (using the percentage of cars allowed to drive on a given day as the instrument) and log household income (using a respondent's years of education as the instrument). All regressions include day-of-week and month-of-sample indicators, lagged percentage of cars allowed to drive, weather and air pollution variables, and respondent gender and a quadratic in age. The level of observation is an individual survey respondent. Parentheses contain standard errors clustered by date. Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Table 9: Ordered Probit Relationships Between Happiness, Congestion, and Income

Dependent Variable:	Self-reported Happiness					
	(1)	(2)	(3)	(4)	(5)	(6)
TPI (congestion)	-0.259*	-0.249*		-0.280**	-0.249*	-0.315*
	(0.101)	(0.101)		(0.107)	(0.108)	(0.150)
Log HH income			0.414**	0.403**		
			(0.140)	(0.153)		
Male		-0.128*	-0.171*	-0.169**	-0.070	0.008
		(0.060)	(0.070)	(0.065)	(0.077)	(0.101)
Age (decades)		-0.424**	-0.316**	-0.324**	-0.500***	-0.303
		(0.136)	(0.122)	(0.131)	(0.153)	(0.169)
Age^2 (decades)		0.049***	0.040***	0.041**	0.056***	0.035*
		(0.014)	(0.012)	(0.013)	(0.016)	(0.017)
Drop weekends/holidays					Y	Y
Drop 2012						Y
Dependent variable m	3.92	3.92	3.92	3.92	3.92	3.97
N	1,195	1,195	1,194	1,194	848	586

Notes: Each column reports results from an ordered probit regression of the dependent variable on the daily TPI and/or log household income. All regressions implement a Rivers-Vuong control function approach that controls for the first-stage residuals using the percentage of cars allowed to drive on a given day and/or a respondent's years of education as the instrument(s). All regressions include day-of-week and month-of-sample indicators, lagged percentage of cars allowed to drive, and weather and air pollution variables. The level of observation is an individual survey respondent. Parentheses contain date cluster bootstrapped standard errors. Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$.

Table A1: Relationship Between Share Cars Allowed and Weather

Dependent Variable:	Rainfall	Temperature	Humidity	Pressure	Sunshine	Max Wind Speed
	(1)	(2)	(3)	(4)	(5)	(6)
Percent cars allowed	0.17	-3.3	-0.1	0.5	-2.2	-0.3
(*tailpct*)	(2.52)	(4.9)	(0.5)	(3.4)	(1.5)	(0.6)
Dependent variable mean	18.73	106.7	57.4	10,163.8	56.6	45.5
N	1,195	1,195	1,195	1,195	1,195	1,195

Notes: Each column reports results from a regression of the dependent variable on the percentage of cars allowed to drive on a given day and day-of-week indicators. The level of observation is an individual survey respondent. Parentheses contain standard errors clustered by date. Significance: * p<0.05; ** p<0.01; *** p<0.001.