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Does rush hour see a rush of emotions? Driver mood in conditions likely to exhibit congestion

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Abstract

Polls show that a large portion of the public considers traffic congestion to be a problem and believes a number of policy interventions would ameliorate it. However, most of the public rejects new taxes and fees to fund these improvements. This may be because of a disconnect between the public's stated antipathy towards congestion and the recalled emotional costs congestion imposes. To explore this, we use a large and representative sample drawn from the American Time Use Survey to examine how drivers experience four emotions (happiness, sadness, stress, and fatigue), plus a constructed composite mood variable, when they travel in peak periods, in large cities, in city centers, and in combinations of these. We also explore the interactions between these indicators and trip duration. We find evidence that drivers in the largest cities at the very peak of rush hour (5:00pm-6:00pm) are in a less positive mood, presumably because of congestion. However, this effect, though significant, is small, and we find no significant results using broader definitions of the peak period. In all, our findings suggest that congestion's impact on drivers as a group is quite limited. This may help explain why the public's attitude toward painful financial trade-offs to address congestion is lukewarm.

INTRODUCTION

Without question, traffic congestion comes with considerable costs. The Texas Transportation Institute (TTI) (Schrank et al., 2012) finds the average peak period urban auto traveler experiences 38 hours of delay annually, up from 16 hours in 1982. This results in 19 extra gallons of fuel consumed per year, 380 additional pounds of CO₂ created per year, and an average annual cost (in fuel and time) to the peak traveler of \$818. The TTI estimates total congestion costs at \$121 billion per year, with 56 billion pounds of additional CO₂ emissions. Moreover, many of the costs of congestion are difficult to quantify (including decreased travel time reliability and delays in goods movement), probably making these cost estimates lower bounds.

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Another cost that is difficult to measure, but of great importance, is the emotional toll congestion takes. To anybody who has been stuck in traffic, it seems self-evident that congestion breeds frustration. However, there is little empirical evidence on whether congestion is actually creating an unhappy driving public using a broad U.S. sample. This paper aims to fill this lacuna.

This issue is important, because policy responses to congestion come with costs. The popularity, and likelihood of adoption, of road improvements, adding transit service, or sending price signals to discourage driving is dependent upon the public's perception of congestion's impact on their lives.

We posit that driver attitudes towards congestion are not primarily shaped by fuel costs, as it is difficult for a motorist to calculate how congestion contributes to these payments. Additionally, it is difficult for motorists to calculate environmental costs such as congestion's contribution to emissions, and in any event many motorists may remain apathetic about these. Instead, perceptions of the costs of congestion likely come from 1) the opportunity cost of additional travel time, and 2) the emotional discomfort experienced while fighting congestion. It is the latter factor that this paper will measure.

LITERATURE REVIEW

Motorist Opinion on Congestion and its Remedies

One recent survey (Atlantic Media and Siemens, 2014) tells a somewhat ambiguous story about how the public perceives congestion: 22% overall say it is a “big problem,” 29% say it is a “small problem,” and 48% say it is “not a problem.” Moreover, congestion is disproportionately perceived to be a problem in urban areas (25% say it is a “big problem” and 35% say it is a “small problem” compared to 20% and 27%, respectively in non-urban areas). Still, more than half of the public aver that congestion is a public policy problem, at least to a degree.

Moreover, on an individual level there is evidence that many motorists are willing to pay a great deal to avoid congestion. Janson and Levinson (2014) study the behavior of drivers using Minnesota's high-occupancy toll lanes and found that users are willing to pay between \$60 and \$124 in tolls per hour of travel time savings, an amount far higher than commonly used estimates for the value of time.

Given that a large portion of the public perceives congestion to be a problem, what does the public believe should be done? Survey data indicate that they believe numerous policies would have an impact (Table 1): With half of the public believing congestion is a problem, and a majority believing that every policy listed above would help remedy it, it would seem that large-scale investment in the transportation system should be underway. Yet the public rejects this, and other measures to reduce congestion, if they involve painful sacrifices. In the Atlantic Cities/Siemens (2014) poll, only 17% supported, and 77% opposed, raising parking prices. In a Reason (2011) poll, only 19% favored increases in the federal gas tax, while 77% opposed such an increase. A similar poll by Gallup in 2013 found that 66% of people would vote against a state law that would increase gas taxes in order to improve roads or

build more mass transportation (Brown, 2013). A 2006 survey by the AAA finds tepid support for tolls on new roads (39%), tolls on existing roads (33%), increased fuel taxes (21%), vehicle-miles taxes (21%), and increases in non-transportation taxes (e.g., sales taxes or income taxes) for transportation purposes (19%) (AAA Market Research, 2006, as cited by Zmud and Arce 2008). These results are even more striking when keeping in mind that about five percent of American households do not own an auto (Renne and Bennett, 2014); given that all of these policies involve taxing drivers only it would seem that non-drivers should strongly favor new fees and taxes to fight congestion. This suggests that an even higher percentage of drivers oppose these policies.

If the public avers that congestion is a problem, but refuses to make sacrifices to ameliorate it, an important question arises: Are drivers as a group truly bothered by congestion?

Travel Time and Mood

A body of literature addresses this question. First, several studies examine links between mood and travel time, which is increased due to congestion. Some conclude that life satisfaction is lower in those with lengthier commutes (Choi et al., 2013; Morris, 2011; Stutzer and Frey, 2008), and that satisfaction with commutes is lower for those with longer commutes (Olsson et al., 2013; Ory et al., 2004; Ory and Mokhtarian, 2005; Stokols et al., 1978). A number of studies suggest this dissatisfaction is in part caused by elevated stress levels on long trips (Evans et al., 2002; Evans and Wener, 2006; Gatersleben and Uzzell, 2007; Gottholmseder et al., 2009; Kluger, 1998; Koslowsky et al., 1996; Sposato et al., 2012; Stokols et al., 1978; Wener et al., 2003; Wener and Evans, 2011). On the other hand, some work concludes that individuals generally prefer a commute of modest duration over a very long or very short one (Ory et al., 2004; Páez and Whalen, 2010; Redmond and Mokhtarian, 2001). The balance of opinion is that trips of longer duration are more stressful, suggesting that, to the extent that congestion contributes to increased travel times, it is deleterious to our emotional lives.

Congestion and Stress

Other work has focused on the direct emotional impact of driving in traffic. Three studies of bus drivers find traffic congestion is a problem due to increased stress (Duffy and McGoldrick, 1990; Evans et al., 1999; Evans and Carrère, 1991); this is measured using self-reports or stress biomarkers such as blood pressure or heart rate. Non-professional drivers interviewed in high-congestion conditions also exhibit elevated levels of stress, including frustration, aggression, irritation, and negative mood (Hennessy and Wiesensthal, 1999, 1997). Hennessy and Wiesensthal (1999) suggest this is caused by both travel time increases and, probably, the frustration of driving in congestion. Congestion may also potentially induce stress due to the fact that it causes travel time unpredictability (Evans et al., 2002). High congestion is associated with reduced persistence at solving problems (Novaco et al., 1979; Stokols et al., 1978; White and Rotton, 1998) and proofreading skills (Schaeffer et al., 1988).

A study in southern California found that ridesharing mitigated some of the effects of commutes on stress (Novaco and Collier, 1994). It is possible that ridesharing is less

stressful because of: 1) a shared distribution of driving responsibilities, and 2) pleasure from interacting with another. Our data enables us to examine this.

Our Contribution to the Literature

This study contributes to these lines of inquiry in a number of ways. First, we examine the relationship between congestion and emotions that have not been observed before (happiness, sadness, and fatigue, in addition to the more commonly studied stress). Second, we consider the separate impacts of delay and non-delay emotional stimuli. Third, unlike previous work, which generally utilizes small samples in restricted geographies, we have a large, geographically-diverse sample of drivers (over 14,000) drawn from the entire nation. Finally, our study differs conceptually from prior work in that we do not directly observe exposure to congestion, which would be extremely difficult to do given a sample as large as ours. Instead, we observe whether drivers reside in large metropolitan statistical areas (MSAs) and in central areas within MSAs, and whether they are traveling at the peak time periods. These conditions are strong predictors of congestion, but because we do not observe individual exposure we can only indirectly infer whether congestion produces negative emotions at an individual level. However, our data are ideal for answering our question of interest—How does congestion shape the political attitudes of drivers as a group?—because we take into account that many drivers, even those in the most congestion-prone times and places, do not experience congestion at all and thus may not be moved to take political action to ameliorate it.

DATA

Our data are drawn from the American Time Use Survey (ATUS) (Bureau of Labor Statistics, n.d.), which is conducted by the Bureau of Labor Statistics and the Census Bureau. Our sample represents a broad cross-section of the population; the survey population includes all Americans over 14 years of age who are not in the military or residing in institutions. The ATUS interviews roughly 13,000 households each year. Interviewers aid the respondents in reconstructing time spent on activities on the day prior to the survey. Respondents are also queried about where activities were undertaken, including travel mode. Our models focus on instances of driving; we have roughly 14,000 such cases in our sample. The survey also collects sociodemographic data commonly included in social science model specifications, and location data is added by the Census Bureau.

In 2010, 2012 and 2013 the ATUS conducted a well-being module. It sampled three activities per respondent per day and asked about the level to which they felt four emotions (happiness, sadness, fatigue and stress) during each. This method is similar to the Day Reconstruction Method (DRM) of gauging affect, a technique developed by Nobel Prize-winning happiness economist Daniel Kahneman (Kahneman et al., 2004).

There is debate about the DRM and whether it is comparable to its primary alternative, the Experience Sampling Method (ESM) (see Hektner, Schmidt and Csikszentmihalyi, 2007), in which subjects carry a device (for example a cell phone) which signals them at regular or random points during the day and collects reports on activity and emotions in real time. The ESM has clear advantages in that it does not involve recall bias. However, despite the fact

that technology is advancing, it is burdensome for respondents; is costly, making it very difficult to collect a sizeable sample; can miss rare activities; and introduces potential error by making the subject highly conscious of being monitored.

The DRM was developed to overcome these limitations. It may be less burdensome for respondents as it does not involve frequent interruptions throughout the day and can easily construct mood for all activities through an entire day. Also, it is less costly than equipping participants with devices (e.g., smartphones).

The DRM's has been widely used; the paper introducing it (Kahneman et al., 2004) has nearly 900 citations. Also, there is evidence that it produces results which are comparable to ESM studies, and similar results have been obtained in studies where both techniques are used (Bylsma et al., 2011; Grube et al., 2008). There are correlations between DRM and ESM scores of roughly between .35 and .61, varying by emotion.

Probably the biggest potential problem for the DRM stems from memory recall. A day later, subjects may forget the intensity of their feelings during the activity, or may give false scores because they stereotype the issue in question. For example, subjects may give high scores for activities they typically enjoy even if it was less pleasant on the prior day. Retrospective measures like the DRM may be more likely to reflect the peak of the experience, either positive or negative, and may be more likely to pick up the last emotion felt (Diener and Tay, 2013; Fredrickson and Kahneman, 1993). The DRM can produce emotion scores that are somewhat attenuated compared to those from ESM, perhaps due to recalled emotion being less intense than experienced emotion (Diener and Tay, 2013). Moreover, the scores from DRM seem to reflect mildly more positive mood than ESM's (Bylsma et al., 2011).

There are several more general caveats about the study of mood, whether by DRM, ESM or some other method. One is that emotions may vary considerably within any given activity; for example, many trips observed in this paper undoubtedly feature congested stretches and uncongested stretches, with mood varying across the journey (Diener and Tay, 2013). Another issue is that emotions may be affected by other activities that happen before or after the activity in question. Those with more activities may respond differently than those with fewer. Finally, results will vary based on the emotions chosen and the words used to describe them.

However, overall, the DRM (and by extension the ATUS study) is a useful tool. Diener and Tay (2013), who review evidence on its validity and reliability, conclude that, while more study is needed, DRM is still a "promising method." Moreover, for this paper, the main issue with DRM—potential recall error—is actually a strength and not a weakness, as we discuss below.

CONCEPTUAL FRAMEWORK

We present twenty-five ordinary least squares (OLS) regression models, with the following five specifications for each of five emotions. Note that new terms added to each model appear in **bold**.

- (1) $\ln E_i = \beta_1 P_i + \beta_2 C_i + \beta_3 L_i + \beta_4 DE_i + \varepsilon_i$
- (2) $\ln E_i = \beta_1 P_i + \beta_2 C_i + \beta_3 L_i + \beta_4 TP_i + \beta_5 I_i + \beta_6 DE_i + \varepsilon_i$
- (3) $\ln E_i = \beta_1 P_i + \beta_2 C_i + \beta_3 L_i + \beta_4 TP_i + \beta_5 I_i + \beta_6 P_i^* C_i + \beta_7 P_i^* L_i + \beta_8 C_i^* L_i + \beta_9 DE_i + \varepsilon_i$
- (4) $\ln E_i = \beta_1 P_i + \beta_2 C_i + \beta_3 L_i + \beta_4 TP_i + \beta_5 I_i + \beta_6 P_i^* C_i + \beta_7 P_i^* L_i + \beta_8 C_i^* L_i + \beta_9 P_i^* C_i^* L_i + \beta_{10} DE_i + \varepsilon_i$
- (5) $\ln E_i = \beta_1 P_i + \beta_2 C_i + \beta_3 L_i + \beta_4 TP_i$
 $+ \beta_5 I_i + \beta_6 DU_i + \beta_7 P_i^* DU_i$
 $+ \beta_8 C_i^* DU_i$
 $+ \beta_9 L_i^* DU_i$
 $+ \beta_{10} P_i^* L_i^* DU_i$
 $+ \beta_{11} L_i^* C_i^* DU_i$
 $+ \beta_{12} P_i^* C_i^* DU_i$
 $+ \beta_{13} P_i^* L_i^* C_i^* DU_i$
 $+ \beta_{14} DE_i + \varepsilon_i$

E , our dependent variable, represents, in different models, four observed emotions: happiness, sadness, stress, and fatigue. These are self-reported by ATUS respondents on a 0-6 point scale, with 6 representing the strongest intensity of the emotion. Moreover, we construct a fifth, latent variable representing mood in the aggregate, using a method that follows Bradburn (1969) and Kahneman et al. (2006): the Affect Balance Scale (ABS). The ABS is derived by subtracting the mean of negative emotions (in our case, sadness, fatigue, and stress) from the mean of positive emotions (in our case, happiness); it has been shown by Bradburn to be reliable as a predictor of self-rated happiness. Constructing an ABS variable with our data yields an overall mood score on a six to negative six scale, with a score of six reflecting the best possible mood. However, there are two shortcomings of this method. First, positive and negative affect “may not lie on a single dimension,” and, second, “calculating a difference score substantially lowers internal consistency reliability” (Diener and Tay, 2013, p. 260). Cronbach's Alpha for the four emotion variables used here is .647.

As is typical in happiness research, since most people report themselves to be quite happy (Diener and Diener, 1996; Pew Research Center, 2006) the distributions of our emotion variables are skewed. Thus, all outcome variables were log-transformed after adding one to avoid taking the log of zero, with the happiness and overall mood scores then being reflected (subtracted from 7), and the result then being multiplied by negative one so that a more positive score reflects a greater intensity of the emotion.

We do not observe the congestion our drivers encountered during their trip. Rather, we utilize variables that indicate whether they traveled in places and at times likely to exhibit congestion. The first, P , is a dichotomous variable representing whether the activity was conducted during the peak traffic period. We base our definition of the traffic peaks on data from the TTI, as is shown in figure 1.

Our preferred definition of the peak period is trips beginning between 7:30am and 8:30am, or between 5:00pm and 6:00pm, on weekdays excluding holidays. We also use different

definitions of the peak in sensitivity tests described below, including both broader and more narrow windows.

We include a variable reflecting subjects' MSA population (L) as taken from the ATUS-X extract builder (Hofferth, Flood & Sobek, 2013). Nationwide, there is a strong relationship between congestion levels and MSA population (Table 2). Respondents in large MSA's experience considerably more delay, even on a per capita basis, than their counterparts in smaller places. Seventy-seven percent of peak period vehicle-miles-traveled (VMT) in large urban areas are in congested conditions, versus only 15 percent in small urban areas, and presumably very little in non-MSA areas. Hence L is a dummy variable reflecting whether the subjects live in MSAs of 2,500,000 or larger. Roughly 40 percent of our sample resided in such MSAs.

For our third indicator of congestion, we utilize data on whether respondents reside in center cities (C) as opposed to suburban areas or non-MSA areas. It is reasonable to assume that non-MSA residents experience little congestion. Despite increasing suburban traffic congestion in the second half of the 20th century, overall, center cities probably still experience more congestion problems, with suburbanites enjoying higher travel speeds and less time spent in congested conditions (Deakin, 1990), though evidence on city/suburb congestion differentials is limited.

In addition to the inclusion of P , L , and C in all models, we interact each combination of these variables ($P*C$, $P*L$, and $C*L$) in models 3-5 to examine whether there is an additional influence from experiencing two congestion indicators simultaneously. For example, the $P*L$ term allows driver emotions to be less positive during peak periods in large cities than during peak periods in smaller places, or, conversely, less positive in large cities during the peak as opposed to in large cities outside the peak. This is important because the spatial and temporal distribution of congestion outlined above shows that congested conditions are strongly associated with travel that is both at the peak and in large cities. For this reason, $P*L$ was the term we hypothesized would exhibit the most significant association with mood. In Model 4 we add the interaction of all three of these terms ($P*C*L$).

The ATUS classifies travel by trip purpose (TP), which we add in Models 2 and higher. This is a vector of dummy variables representing the ATUS' 16 major trip purpose categories. The work trip purpose is separately broken out in the tables below because it accounts for a disproportionate share of travel in the congested peak periods: 41% of peak trips in our sample were for work purposes, versus only 19% for off-peak trips. It is important to control for work trips, as past research shows that they may elicit strong emotions (Kahneman and Krueger, 2006; Morris and Guerra, 2014; Olsson et al., 2013; Ory et al., 2004; Ory and Mokhtarian, 2005; Páez and Whalen, 2010; Redmond and Mokhtarian, 2001; White and Rotton, 1998). Most evidence suggests the work trip is unenjoyable; thus it is important that negative feelings related to the commute are not conflated with negative feelings due to traveling at a time likely to see significant congestion.

Vehicle occupancy data show that commutes are more solitary than other trips. According to the 2009 NHTS, vehicle occupancy for work trips is 1.2 persons per vehicle, versus 1.8 for

shopping and personal business trips, and 2.2 for social and recreational trips (Davis et al., 2014). Since prior research shows that interacting with others is generally associated with positive emotions (Morris and Guerra, 2014), and since the effect of the solitary nature of peak period driving should not be conflated with emotions caused by peak period congestion levels, in Models 2 and higher we control for whether drivers were interacting with another person (*I*).

In our final specification (Model 5) we include a variable that reflects trip duration (*DU*). Since one of the major costs of congestion is increased travel time, we do not control for this variable in our basic models since doing so would understate congestion's negative impact on emotions. However, it is instructive to include this variable in a separate model to see what portion, if any, of the observed negative impact of travel in likely-congested places is due to factors other than delay, such as the disutility of having to operate the vehicle in stressful conditions. Model 5 also includes the full set of interactions between duration, peak period, center city location, and large city residence size to see if long trips are particularly onerous in likely-congested conditions.

In addition, we include a vector of personal characteristics (*DE*) identified from prior research as affecting life satisfaction (such as Dolan et al., 2008). These include (with our findings of significant impacts on overall mood in parentheses): sex, age and age squared, marital status (married with spouse present +, married with spouse absent –) income normalized by family size (–), number of children (–), Hispanic (+), black (+), Asian (+), non-citizen (+), employment status (full-time worker –), and years of education (–). It should be noted that while prior research on life satisfaction has unearthed meaningful associations between it and life circumstances, there is generally weak correlation between life circumstances and mood (Diener and Tay, 2013). This may be because mood measures are insufficiently sensitive, because life satisfaction measures are biased, or because immediate mood is simply less affected by things like income or marriage than a cognitive appraisal of overall life circumstances is.

RESULTS

Table 3 presents results for models with the overall mood variable as the dependent. In Model 1, mood is not significantly associated with a trip taking place in the peak, being in a large city, or being in a center city. Interacting with another is associated with a more positive mood in Models 2 and higher, but there is no significant link between the work trip purpose and mood.

Model 3 shows that for peak period drivers, city size or location within the city have no additional significant effect on mood. The same is true for the association of large city residence with drivers in a particular location. Model 4 finds that the three-way interaction between peak period, large city, and center city location is also insignificant. In short, after controlling for relevant covariates, drivers in conditions that are likely to feature congested traffic are in no measurably different mood than those who are not.

Model 5 examines the effects of trip duration. As expected, long drives are associated with a significantly poorer mood. However, none of the interactions of duration with the congestion indicators are significant. This suggests long trips are associated with no better or worse mood depending on whether they are in places and at times likely to feature congestion.

We also examined the four emotions individually (see supplemental tables S1-S4). In terms of stress, with the exception of higher stress levels on trips of longer duration, none of the variables of interest are significant, suggesting stress is no higher in likely-congested places than outside of them. Fatigue Models 2, 3, and 4 indicate that the work trip is associated with less fatigue; we have no immediate explanation for this, except to note that the peak period timeframe, in which a large share of work trips take place, is controlled for, so this finding is after accounting for the time of day in which work trips normally take place. While highly speculative, drivers may feel more fatigue on non-work trips because they are taking up valuable time that could be spent in other leisure activities. In Model 5 there is a borderline significant association between fatigue and the interaction between peak and large cities, as might be expected if one hypothesizes that travelers in congested places would, as a group, exhibit greater fatigue. However, the relative weakness of the association, plus the lack of significance for this association in Models 2 through 4, makes us hesitant to declare this a convincing finding.

Model 5 suggests that center city drivers are less sad than others (the main effect), but that their sorrow significantly rises with long trip duration. However, the latter effect is fairly trivial in magnitude, with peak period drivers being predicted to become less sad than other drivers with a trip duration of over 525 minutes. Given the small magnitudes of these effects, the fact that the key interaction terms (especially Peak*Large City) are insignificant, and the lack of a convincing explanation as to why peak period drivers might be less sad than others, we regard these findings as essentially null. For happiness, no variable is significant with the exception of interaction with others, which has a strong and positive association.

Examining Alternate Definitions of the Peak Period

In sensitivity tests, we redefined the peak period. Our preferred period was non-holiday weekdays between 7:30am-8:30am or 5:00pm-6:00pm. We alternately explored a broader peak (6:30am-9:30am or 3:00pm-6:30pm) and two narrower windows (between 8:00am-8:30am or 5:00pm-5:30pm, and between 5:00pm-6:00pm). The narrower windows were selected based on the TTI data to reflect times with the absolute peak of congestion.

We ran all of our model specifications for the five emotions and each peak definition. There was one set of significant results for the peak period*large city interactions using the narrowest time window (Table 4, results for Model 3).

Thus for large city travelers, mood was significantly less positive for those traveling in the 5:00pm-6:00pm window, which according to the TTI is likely to exhibit the heaviest traffic. This is primarily due to higher stress, higher sadness, and, arguably ($t=1.87$) higher fatigue. Absent any convincing alternate narrative as to why drivers in the most congested place at the most congested time are experiencing these emotions, and given findings in the prior

literature about the link between congestion and stress, it seems likely that these effects are indeed caused by traffic congestion.

DISCUSSION

We thus find a link between driving at the “peak-of-peak” times and in the places (large cities) that feature the most intense traffic, which, in concert with the findings of the prior literature, probably reflects the impact of traffic congestion on drivers. However, the strength of evidence for this finding is limited. None of the t-statistics are greater than 3, and the actual effect sizes are small, with parameter estimates indicating that being a peak, big city driver, as opposed to an off-peak small place driver, results in 7.6 percent more negative affect on the 1-13 scale, with 13 being the most negative mood. (Note this calculation takes into account the main effects for peak and large city driving as well as the interaction effect between them.)

Moreover, this effect is only observable using a narrow definition of the peak. This means that these negative emotions are only manifested in a small number of drivers; only 2.61 percent of our instances of driving were between 5:00pm and 6:00pm on a non-holiday weekday in an MSA of over 2,500,000 persons. Moreover, these results only became apparent in one of many sensitivity tests. While there were 4 cases of significant results for our preferred congestion indicator (large city*peak), there were 136 other permutations of time periods, congestion indicators and indicator interactions, and emotions that produced null results.

The general lack of significance for our congested place indicators is noteworthy given the large sample size employed here. With over 14,000 cases of driving, significance should be detectable even given modest effect sizes. In fact, in results not shown, we do observe significant associations between many activity types and mood—as might be expected, work, school, using personal services, and engaging in personal care are associated with negative mood, while caring for others, eating and drinking, engaging in sports and leisure, socializing, and participating in religious activities are associated with positive mood—so the instrument does reliably register mood in many cases where it is expected to exist.

Thus, while we have identified the fact that drivers in the times and places most likely to experience congestion experience slightly degraded mood, we do not find that the driving public in likely-congested places as a whole manifests strongly negative feelings compared to those in likely-non-congested places.

There are, of course, several caveats that should be noted. First, the center city variable may be problematic, both because the data suggesting center cities are more congested is limited and because much of center city residents’ travel may be outside the center city (the average vehicle trip distance according to the 2009 NHTS is about 10 miles (Santos et al., 2011)). On the other hand, TTI data strongly suggest that peak period travel in large cities is very likely to exhibit congestion, while off-peak travel in small places is not.

In addition, we may not be observing all emotions of interest; it is possible that other negative emotions (including “frustration,” “anger,” “annoyance,” and “impatience”) may be

more closely linked to traffic congestion than, say, sadness is. Also, there may be residual confounding from a wide variety of individual or environmental factors. Previous work suggests that some personality characteristics, such as aggressiveness, may play a role in whether traffic congestion causes stress (Hennessy and Wiesenthal, 1999, 1997; Mesken et al., 2007). Additionally, other environmental factors, including billboards and freedom to choose lanes have been shown to be associated with travel satisfaction (Ettema et al., 2013; Stephens and Groeger, 2009). As was noted above, we do not observe how emotions vary within the trip, but only respondents' best effort to aggregate emotions afterward. This may result in reporting based on peak or last emotion, not mood throughout the whole activity.

This leads to the first of two other important issues. Our use of a retrospective measure raises the issue of recall bias. Although the time lapse between the experience and the reporting of it is not large (one day), as was discussed above, ESM and DRM findings, while correlated, are not correlated perfectly. It is highly likely that we remember our emotions differently than we experience them. Hence, real-time reports of emotion may have been more accurate were we directly studying how congestion affects emotion. However, for the purposes of this paper, a retrospective measure is actually preferable. We are most interested not in measuring how congestion affects emotion but in how driver perceptions of congestion affect their preferences toward public policy congestion solutions. We prefer this retrospective measure because when drivers form and express these political preferences they are relying on their memory, however imperfect, of how congestion affects them.

Second, we do not observe congestion directly but instead indicators of where congestion is likely to exist. Again, were we most interested in studying congestion's effect on emotions this would be a shortcoming, because although the data suggest a large majority of peak period big city travel takes place in congested conditions, our population of such drivers will include some who do not experience congestion. However, for the purposes of understanding why drivers as a group, including those who do not experience congestion personally, do not support costly measures for congestion relief, our indicators are actually preferable.

CONCLUSION

In light of prior evidence, plus the seeming intuitiveness of the proposition that congestion breeds frustration, how can the findings of a quite tenuous link between emotions and driving in the places most likely to be congested be explained?

First, mood and life satisfaction are both complex phenomena shaped by myriad factors. Our models control for many important ones, including wealth, employment, and family structure. Given that the R^2 of our overall mood models are in the neighborhood of .07, it is clear that many other factors of import are unobserved, including things like the harmoniousness of family life, job satisfaction, and the genetic predisposition to happiness, which has been shown to predict between one-third and one-half of life satisfaction (Lykken and Tellegen, 1996; Nes et al., 2006). Also, we do not observe the other events experienced during the study day, which may affect mood. In light of the fact that so many factors shape mood, it is perhaps unsurprising that traffic congestion plays a relatively minor role.

The muted impact of the conditions of travel on emotions has been documented in other research; for example Morris and Guerra (2014) find differences in mood based on travel mode are not dramatic. If, as they find, the difference between walking and bus travel is not significant, it is unsurprising that the difference between driving in congested and uncongested places is not either.

Another possible explanation is the “hedonic treadmill” theory (Brickman and Campbell, 1971). According to this perspective, changes in our circumstances might provoke immediate shifts in happiness levels, but over time, as we become inured to our condition, these impacts fade and we return to our base happiness “set points.” For example, research has shown that lottery winners and accident victims are no more or less happy than others (Brickman et al., 1978). Perhaps individuals exposed to high congestion levels on a frequent basis simply become inured to their state.

Additionally, individuals likely alter their behavior based on their feelings about congestion. It is probable that at least some individuals adjust work schedules or travel routes to avoid conditions likely to be congested. For the most part, those who do so are likely to be individuals who dislike congestion intensely, while those who mind congestion less may be less willing to alter their behavior. Alternately, driver may be people who are more willing to transform their experience of congestion by listening to entertainment (e.g. news or audiobooks) to fill the time. For this reason, this paper reflects the feelings of those who actually travel in conditions likely to feature congestion versus those of other drivers, but not what the response of the average driver would be if he were placed in a congested versus an uncongested setting.

Also, it is possible that some of the public does not fully understand the extent to which congestion itself makes them unhappy. This may help explain the dissonance between our findings and much of the extant literature. When congestion levels are brought to their attention, for example by frequent inquiries about emotions during a drive, many people may voice irritation with the phenomenon. But these emotions may ultimately be highly transitory, not ultimately making a lasting impact on their broader overall attitudes. If the negative emotions caused by congestion are quickly forgotten when the trip is over, it may explain why drivers and voters do not support measures to fight it.

One other potential explanation for our findings stems from Taylor's (2002) observation that the density of potential destinations, which is presumed to be higher in the most congested places, might somewhat offset the emotional costs of congestion. Travelers fighting congestion might be rewarded by reaching more emotionally desirable destinations, compared to those in uncongested places who may be traveling to less rewarding places.

Finally, the fact that we are observing all drivers in congested places, not only those who actually are fighting traffic, may help explain lukewarm feelings toward painful sacrifice to fight congestion. This is because survey takers and voters, regardless of their individual exposure, must approve these policies. Hence, our finding that congestion is but a small detractor from the moods of drivers in the aggregate in the largest cities at the most congested times, and that it does not contribute to poor mood in any place but in the largest

cities at the absolute peaks, may very well help explain why programs like higher fuel taxes are not particularly popular.

Part of this response is undoubtedly due to psychological bias against having to pay for something that was previously “free”; motorists have been far more willing to accept new HOV or tolled lanes if they are new construction than if they were converted from previously existing general-purpose lanes (Fuhs and Obenberger, 2002). Still, though, travel in congested conditions is not “free” either—motorists pay in time, wasted fuel—and, presumably, frustration. Were those costs high enough, it stands to reason that motorists would demand action, even if it involved sacrifice; for example, the public is willing to pay for new safety technologies such as airbags, lane departure warning, and rear-view cameras, even though going without them was previously “free,” because the trade-off is judged to be worthwhile.

It should be noted that one potential counter-argument against our thesis is that perhaps the public rejects spending to fight congestion not because it opposes it in principle but because it believes the tax money would not be spent effectively. In particular, the public may distrust higher levels of government (i.e., the state and federal governments) but be more open to taxation for improvements when the money is guaranteed to stay local and be dedicated to specific, desirable projects. This would explain why local option sales taxes which are typically earmarked for specific projects (generally involving the expansion of transit service) have tended to pass at the ballot box (Center for Transportation Excellence, 2015).

It might also be argued that although voters as a group express antipathy toward tolls on existing roads to manage congestion (AAA Market Research, 2006, as cited by Zmud and Arce, 2008), the high willingness to pay tolls in practice (Janson and Levinson, 2014) is evidence that congestion is exacting a high cost, at least for many drivers. This may be true, although the high observed willingness to pay may be due to the time costs of congestion and not its emotional toll. Moreover, as Janson and Levinson conclude, their findings may not reflect rational, fully informed decisions on the part of drivers. Since drivers have no information about congestion levels ahead other than the toll level, they are likely to take high toll levels as evidence of severe impending congestion; this may explain Janson and Levinson's finding that contrary to economic logic drivers are more likely to more likely to select the tolled lanes when toll levels are higher. Finally, Janson and Levinson study drivers in congested places, and do not observe peak travelers who are not experiencing congestion.

With all of this said, Taylor (2002) concludes that:

Most transportation researchers...agree that some form of pricing is the best way to reduce metropolitan traffic congestion. But many public officials see toll roads and parking charges as politically risky and unpopular...The traveling public's frosty reception of such serious proposals to reduce congestion suggests to me that people see it as less of a problem than they let on. (p. 12)

Why might this be the case? As Ory et al. (2004) note, it is possible that the large portion of the public expresses concern with congestion in surveys, as is documented above, not because it congestion affects them personally but because they may perceive it to be a

problem due to its effects on others. This may explain a paradox found by Baldassare (2002) in a survey in California, a state notorious for its traffic congestion, where 81 percent reported that congestion was at least somewhat of a problem in their area, but 82 percent said they were very or somewhat satisfied with their personal commutes. Although, as noted above, slightly more than half of the public in general reports traffic congestion is a problem (Atlantic Media and Siemens, 2014), another poll found that only 36 percent agreed with the statement “traffic congestion is a source of stress in my life” (Edmondson, 1998). This may be due to the fact that most individuals do not experience congestion, but it may also be due to the fact that congestion when experienced is not the source of long-term, sustained stress.

These findings are in concord with our conclusion. If congestion is not making even the very small number of drivers who travel in large cities at the peak-of-peak period particularly unhappy, and if that group constitutes a very small share of travelers, the paradox that many Americans complain about traffic congestion yet are unwilling to support most costly measures to address it, at least in the abstract, is unsurprising. While the costs of congestion—in money, environmental degradation, and time—are undoubtedly onerous, in terms of Americans’ day-to-day emotional lives congestion may not be a particularly severe problem.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Source: TTI Annual Mobility Report 2012

Figure 1.
The peak travel periods.

Table 1

Public opinion on the potential impact of congestion-fighting measures.

	Major Impact (%)	Minor Impact (%)	No Impact (%)	Don't Know (%)
Building More Lanes/Roads	38	28	31	2
Upgrading Transit	38	28	30	3
More Bike Lanes	24	34	40	1
Improving Sidewalks	28	35	35	2
Promoting Telecommuting	39	21	24	5

Source: Atlantic Media/Siemens State of the City Raw Data

Table 2

Congestion and urban area size.

	Small Urban Area (<500,000)	Medium Urban Area (500,000-1,000,000)	Large Urban Area (1,000,000-3,000,000)	Very Large Urban Area (>3,000,000)
Annual Hours of Delay	23	29	37	52
Pct. of peak vehicle miles traveled in congested travel	15	37	55	77

Source: TTI Annual Mobility Report 2012

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Table 3

OLS regressions with congestion indicators and trip duration regressed on log of overall mood.

	Model 1 ^a LnMood	Model 2 ^b LnMood	Model 3 ^b LnMood	Model 4 ^b LnMood	Model 5 ^b LnMood
Constant	-1.236 *** (-8.18)	-1.400 *** (-9.27)	-1.408 *** (-9.34)	-1.407 *** (-9.33)	-1.308 *** (-8.70)
Large City	-0.0172 (-0.78)	-0.0168 (-0.79)	-0.00269 (-0.10)	-0.00483 (-0.17)	0.0127 (0.43)
Peak Period	-0.0278 (-1.11)	-0.00209 (-0.08)	0.0400 (1.06)	0.0341 (0.84)	0.0609 (1.59)
Center City	0.0159 (0.70)	0.0164 (0.75)	0.0262 (0.89)	0.0230 (0.76)	0.0250 (0.73)
Work Trip		0.0760 (1.36)	0.0770 (1.37)	0.0763 (1.36)	-0.0444 (-0.79)
Interacting With Someone		0.104 *** (5.04)	0.105 *** (5.07)	0.104 *** (5.06)	0.116 *** (5.71)
Peak*Center City			-0.0349 (-0.68)	-0.0127 (-0.17)	-0.0174 (-0.16)
Peak*Large City			-0.0718 (-1.51)	-0.0582 (-1.02)	-0.0939 (-1.42)
Large City*Center City			-0.0107 (-0.25)	-0.00342 (-0.07)	-0.0444 (-0.85)
Peak*Large City*Center City				-0.0477 (-0.47)	-0.00787 (-0.06)
Trip Duration					-0.000788 ** (-3.29)
Duration*Peak					-0.000315 (-0.92)
Duration*Center City					-0.0000288 (-0.06)
Duration*Large City					-0.000123 (-0.36)
Duration*Peak*Large City					0.000244 (0.23)
Duration*Peak*Center City					-0.000833 (-0.21)
Duration*Large City*Center City					0.000647 (0.78)
Duration*Peak*Large City*Center City					0.000392 (0.09)
<i>N</i>	14336	14318	14318	14318	14318
adj. <i>R</i> ²	0.046	0.074	0.074	0.074	0.084

t statistics in parentheses* $p < 0.05$ **
 $p < 0.01$ ***
 $p < 0.001$ ^a Models control for demographics (sex, age, age squared, marital status, income, number of children, Hispanic, black, Asian, noncitizen, employment status, education).^b Models control for demographics (sex, age, age squared, marital status, income, number of children, Hispanic, black, Asian, noncitizen, employment status, education) and trip purpose.

Table 4

OLS regressions for a narrow peak (5:00pm-6:00pm)

	Model 3 LnMood	Model 3 LnStress	Model 3 LnFatigue	Model 3 LnSad	Model 3 LnHappy
Constant	-1.412 *** (-9.33)	0.586 ** (3.16)	1.227 *** (7.33)	0.417 ** (2.82)	-0.840 *** (-5.86)
Large City	-0.00201 (-0.08)	0.0197 (0.66)	0.00243 (0.08)	0.0123 (0.51)	-0.00181 (-0.07)
Peak	0.0371 (0.73)	-0.0465 (-0.89)	0.0986 (1.82)	-0.0963 *** (-3.44)	0.0306 (0.68)
Center City	0.0197 (0.68)	0.0170 (0.54)	-0.0142 (-0.45)	-0.0327 (-1.35)	0.00524 (0.19)
Work Trip	0.0763 (1.36)	-0.0909 (-1.39)	-0.176 ** (-2.94)	-0.118 (-1.65)	-0.000961 (-0.02)
Interacting With Someone	0.105 *** (5.11)	-0.0210 (-0.91)	0.0268 (1.18)	-0.0619 *** (-3.38)	0.140 *** (6.95)
Peak*Center_City	0.0131 (0.19)	0.0528 (0.70)	0.00594 (0.08)	0.0396 (0.83)	0.0601 (0.95)
Peak*Large City	-0.133 * (-2.15)	0.197 ** (2.70)	0.129 (1.87)	0.101 * (2.10)	-0.00998 (-0.16)
Large City*Center	-0.0121 (-0.28)	0.00601 (0.13)	0.0554 (1.18)	0.0142 (0.40)	0.0160 (0.38)
<i>N</i>	14318	14385	14387	14378	14349
adj. <i>R</i> ²	0.075	0.052	0.065	0.038	0.079

t statistics in parentheses

Models control for demographics (sex, age, age squared, marital status, income, number of children, Hispanic, black, Asian, noncitizen, employment status, education) and trip purpose.

*
 $p < 0.05$ **
 $p < 0.01$ ***
 $p < 0.001$