Other-Regarding Behavior: Theories and Evidence

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Abstract

We use field data on traffic behavior to test and refine existing models of "other-regarding behavior;" that is, behavior that meets social or civic obligations despite the lack of material incentives to do so. We find that existing models relying on methodological individualism fail to match the data. Models of social norms appear to have greater promise. Our ultimate goal is to develop mathematical theories that take as inputs only the material features of an environment, and predict when we should expect people to exhibit other-regarding behavior.

1 Introduction

Individuals meet many obligations of a social and civic nature, despite the seeming lack of material incentives to do so. To a remarkable extent, people vote in national elections, pay their taxes, are helpful to strangers, contribute to charity, and even tip in restaurants. Introspection suggests that we often act prosocially, not because of any enforcement or reward mechanism, but instead because we are directed by a moral compass partly based on social norms. If this is the case, then the rational actor model of economics needs to be amended, possibly in substantial ways. Let us call this type of non-instrumental, prosocial behavior *other-regarding behavior*. Our goal is to develop and test mathematical theories that take as inputs the material endowments and other material features of an environment, and predict when we should expect people to exhibit other-regarding behavior.[1]

Our first hurdle is to establish that people do, in fact, sometimes make other-regarding choices. The problem is that behavior that appears other-regarding can often be interpreted as simply instrumental.[2]

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[1] In our models, primitives are material allocations. So, for example, the state of emotional arousal will not be taken as a primitive, even though it might be measurable. In our model, emotional arousal would be treated as an output—something that the theory should predict.

[2] The fact that most people make no effort to evade income taxes provides a good example of the identification problem: even

This identification problem, added to the general paucity of data regarding social phenomena, makes it difficult to test alternative theories of the emergence of other-regarding behavior. Our strategy is to gather abundant evidence in an environment where other-regarding behavior is likely not instrumental—driver behavior in traffic.

Our data collection records the behavior of motorists who are seeking to leave a highway through crowded exit. Because the exit is crowded, a line forms with drivers waiting to take it. We measure the extent to which drivers orderly place themselves in line, or instead skip part of the line and insert themselves at a point in line closer to the exit. We illustrate how even this simple exercise identifies interesting variation that allows us to discriminate among different theoretical models of other-regarding behavior. Our ultimate goal is to collect further data on motorist behavior in traffic, and to use this rich source of data, combined with evidence from a variety of disciplines, to build a formal mathematical model of other-regarding behavior that improves on the existing ones.

Most of the existing models of other-regarding behavior come from the experimental economics literature. In these models, there is generally no role for social norms. Instead, agents are assumed to derive utility from the material well being of society,[3] and/or from the degree of inequality of well-being within a reference group.[4] It has also been hypothesized that agents are motivated not by the consequences, but directly by the *act* of voluntarily giving.[5] A somewhat different class of models posits that, in addition to their material well-being, agents also wish to be liked, or at least thought well of, by other agents. This psychological effect may stimulate cooperation or sharing.[6] Such models come closer to identifying a "social norm" that underlies behavior. Finally, we are in the process of testing and refining a model of ethical behavior developed by Feddersen and Sandroni (2002) to explain why people vote.[7] This model can viewed as an explicit model of social norms.

The ultimate goal, to which this paper will contribute, is to identify a theory that can explain a variety of other-regarding behaviors—in the same way that the rational agent model is able to account for a variety of economic phenomena. The ideal candidate is a theory that is simple and, at the same time, able to explain why other-regarding behavior is not observed in several circumstances where it might be expected to arise.

though the probability of being audited is minimal, and there is usually no penalty even for those found to have underreported their income, it is still possible that citizens overestimate the probability of being audited, or that they hate being found guilty in the auditing process. (One should also acknowledge that the existing methods of tax collection may prevent most people from avoiding taxation.) To circumvent this identification problem, much of the analysis of other-regarding behavior has taken place in the laboratory.

[3] See, e.g., Andreoni and Miller (2002).

[4] Regarding inequality aversion, see Fehr and Schmidt (1999) and Bolton and Ockenfels (2000).

[5] This is Andreoni's (1990) *warm glow* model.

[6] These are called psychological games in the economics literature. See Charness and Rabin (2002) for an application to experiments.

[7] This model is based on ideas developed by Harsanyi (1977, 1980, 1992), and has later been used by Coate and Conlin (2004) and Coate et al. (2004).

Our evidence suggests so far that a successful theory will have to be a theory of social norms. We believe that our analysis is a starting point towards using quantitative field evidence to identify a general model that rationalizes a large set of behaviors.

1.1 Related Literature

The literature on experimental economics has devoted considerable attention to other-regarding behavior. Models have been developed and calibrated to accommodate the large literature which documents a significant degree of other-regarding behavior in experimental conditions.[8] Our analysis is, in a sense, motivated by this literature. We depart from the experimental approach in that our analysis is carried out in a field setting. The field approach is, at a minimum, a useful robustness check of the results from the lab.[9] As we will see, the evidence we have gathered points towards different models than those that have successfully explained experimental findings. We thus view the field analysis of other-regarding behavior not as substitute, but a useful complement to experiments. One of our goals is to derive predictions about other-regarding behavior that could be tested in the laboratory.

The economics literature on charitable giving is one instance of a field analysis of altruistic motives.[10] Our analysis is designed to complement the findings of that literature by studying "altruistic behavior" in a different environment.

Other-regarding behavior is a central focus of sociologists. According to sociological theories, if people are other-regarding, it is because they adhere to a *social norm*.[11] Social norms are unwritten rules, external to the individual and commonly shared, that prescribe how one should behave in a particular circumstance. Social norms that are socially beneficial, and the institutions that enforce them, have been called "social capital."[12] When social norms run against self interest, they must be enforced to survive. Some social norms are enforced externally, by rewards or punishment informally administered via repeated interaction with members of a social network. There is ample theoretical and empirical consensus that a tight social network

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[8] For overviews of this literature see, e.g., Camerer (2003), and Kahneman and Tversky (2000).

[9] Some phenomena that are apparently robust in the laboratory do not seem to persist in the field (see List (2003) for such an example in the case of the endowment effect).

[10] For an overview of this literature, see Andreoni 2004.

[11] For a detailed treatment of the notion of a social norm, see, e.g., Coleman (1990).

[12] See Coleman (1987, 1990) and Putnam (1993, 2000). In Putnam's words: "For a variety of reasons, life is easier in a community blessed with a substantial stock of social capital. In the first place, networks of civic engagement foster sturdy norms of generalized reciprocity and encourage the emergence of social trust. Such networks facilitate coordination and communication, amplify reputations, and thus allow dilemmas of collective action to be resolved. When economic and political negotiation is embedded in dense networks of social interaction, incentives for opportunism are reduced. At the same time, networks of civic engagement embody past success at collaboration, which can serve as a cultural template for future collaboration. Finally, dense networks of interaction probably broaden the participants' sense of self, developing the "I" into the "we," or (in the language of rational-choice theorists) enhancing the participants' "taste" for collective benefits." (Cited from Putnam 1995).

facilitates external norm enforcement.[13] This literature is not the focus of our research, however, because we are interested in norms that are not enforced by an external mechanism of reward or punishment. Such norms are called *internalized*. Internalized norms are thought to be enforced by an internal sanctioning system which is burned into an individual's conscience and thus makes external sanctioning unnecessary.[14] To the extent that we provide a foundation (a structural model of motivation) for internalized norms that takes measurable primitives as inputs, we believe our research will contribute to this sociological literature.[15]

Social psychologists refer to internalized norms as "personal norms." They have developed theories of "norm activation" that are designed to explain what makes individuals more likely to adhere to a given norm.[16] As we will discuss later, this literature has the potential to contribute to our understanding of the data we study. To our knowledge the question of what norms are expected to arise based on material primitives has received little attention in this literature.

Legal scholars have also been concerned with norm adherence. Much attention has been paid to externally enforced norms,[17] though some models (such as McAdams 1997, Ellickson 2001) could be viewed as models of internalized norms. Posner (2000), in particular, develops a (signalling) model of externally enforced norms, or "non-legal cooperation," to confront the fact that "[m]ost people refrain most of the time from antisocial behavior even when the law is absent or has no force." Our analysis complements this legal research by modeling the forces behind internalized norms and their interaction with formal and informal institutions.

1.2 Choice of Field Environment

The environment that we study, rush hour traffic, has been chosen carefully. One important feature of the environment is that it lacks both repeated interaction and formal modes of enforcement. These aspects translate into an absence of external enforcement mechanisms.[18] In addition, the practical anonymity of motorists, as well as the basic structure of the setting, make it implausible that drivers are behaving so

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[13] Greif (1993), Fafchamp (1996), Ellickson (1991), for instance, all report compelling evidence of external enforcement of socially beneficial norms. The empirical debate currently turns on the quantitative importance of such norms (see, e.g. Miguel et al. 2005 for an application to development) and on how easy it is to empirically disentangle the effects of social norms from other competing explanations (see Durlauf and Fafchamps 2004 for a review of this literature). On the theoretical side, there is an enormous literature modeling the emergence of externally enforced social norms, straddling economics (see, e.g., Abreu et al. 1990, Bernheim 1994, Akerlof 1980), legal studies (see e.g. Ellickson (1991, 2001); Posner (2000); and McAdams (1997)), sociology (see Coleman 1990).

[14] For the notion of internalized norm, see e.g. Coleman (1990) and Schwartz (1977).

[15] We recognize that internalization of a norm may derive from past external enforcement of that norm. A history of enforcement may help explain why norms are prevalent in some environments and not in others. It does not, however, help explain the variation observed in our data.

[16] Schwartz (1977), Schwartz and Howard (1981), Cialdini et al. (1990).

[17] See Ellickson (2001) for a review of this literature.

[18] In our environment, skipping the line does not generally constitute a violation of the rules of the road. Moreover, the particular setting we study, described in detail below, precludes most forms of material punishment by other drivers; and we find no evidence of the permissible forms of punishment (skipping ahead of a driver who skipped) in the data.

as to elicit material rewards from others. A second important feature of the environment is that subjects (motorists, in our case) are familiar with the setting and with the existing social norm (if any).[19] In this respect, field settings may have some advantages relative to the laboratory, particularly if we are concerned about our ability as researchers to control the factors and cues in the lab that might activate a specific social norm in subjects. At the same time, we wish to preserve many of the desirable features of laboratory experiments, first and foremost, a relatively simple strategic interaction; in the case of traffic, we are able to project the agent's decision problem into a simple one: how much of the line to skip.[20] A third feature of this environment is that, to the extent that we observe other-regarding behavior, we can be relatively certain the behavior is permanent, not transient. We want to avoid a situation in which, once the subjects realize the material costs and benefits of the environment in which they operate, their behavior converges towards self-interest. Since many of our subjects are presumably commuters who take the same route for years, we can discount the effect of transient behavior. Finally, by studying traffic behavior we can obtain many observations at low cost, and potentially collect data from related experiments in different geographic locations, times of day, or slightly different conditions (different shapes of intersection, length of the line, etc.) The combination of these features, we believe, makes behavior in traffic a good testing ground for theories of other-regarding behavior.

2   Description of Data Collection

To evaluate alternative theories of other-regarding behavior we analyze choices in a traffic environment that is familiar but, nevertheless, sufficiently rich as to permit a variety of behaviors. The environment we study, depicted in Figure 1, is the confluence and subsequent divergence of three distinct sources of traffic labeled routes A, B and C. At the juncture of the three "source routes," three lanes (L, M and R) are formed. Prior to this juncture, motorists may travel only on their source route. After the juncture, however, motorists from any of the sources A, B or C, may travel in any of the lanes L, M, or R; and motorists may switch back and forth between lanes. The dotted lines in Figure 1 indicate areas in which lane-switching is possible. After a substantial distance, the three lanes split again into two routes, A' and B', each with a distinct destination.

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[19] Given the time at which we record our data (between 4:30 and 6:00 P.M.) and the location, we conjecture that most of the drivers in our sample are commuters, who are therefore presumably familiar with the norms. This reduces the concern that drivers may be watching others to determine what the norm is on that particular stretch of road. For an intriguing field experiment suggestive of this effect, see Cialdini et al. (1993).

[20] It must be acknowledged that, relative to experimental evidence our data have the shortcoming that we cannot repeatedly observe the behavior of a single agent.
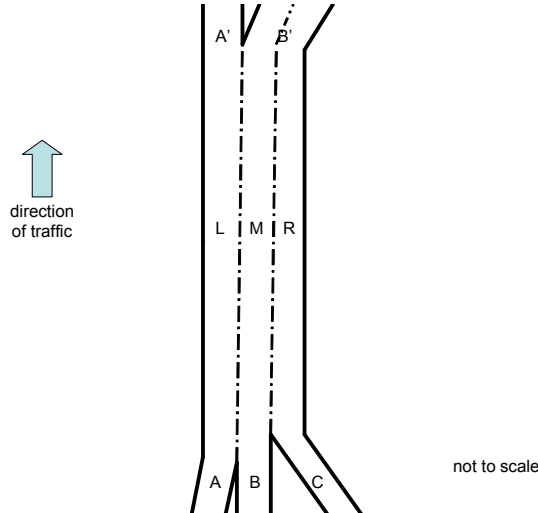
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Figure 1: Depiction of Traffic Environment

2.1   Specifics of the Data

The data are drawn from an example of the above-described traffic environment located in King of Prussia, Pennsylvania. In these data, route A is an exit ramp from Interstate 76 West; route B is a local route from King of Prussia Shopping Mall; and route C is I-76 East.[21] At the other end of the confluence, route A' is Route 422 West and route B' is East Swedesford Road. The distance between the juncture of routes A, B and C, and the subsequent divergence of routes A' and B' is approximately 0.75 miles. The results described below are derived from observations of traffic at this location on seven different weekdays. On each of these days, the relevant traffic was observed for between 45 and 90 minutes around the rush-hour period (between 4:30 P.M. and 6:30 P.M.). The traffic was observed and recorded via a remote-controlled video camera located on a street lamp just above the juncture of routes A,B and C. The location of the video camera precludes thorough analysis of the traffic emanating from source route B, so we focus on traffic from the remaining two source routes only.[22] Summary statistics of the observations are presented in Table 1.

A typical rush hour traffic pattern is depicted in Figure 2 below, where each shaded oval represents a separate vehicle. There are several notable features of the typical rush-hour pattern. First, traffic in lane L and in its primary source route, A, is thick and very slow moving. Despite spanning a distance of less than a mile, the average time required to travel in lane L from the point X to point Z during rush hour is approximately 9 minutes, and is often substantially longer. Second, traffic in lanes M and R is thin and

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[21] The juncture of these three routes is directly across from the Home Depot located at 1300 East Dekalb Pike, in King of Prussia, Pennsylvania.

[22] We can observe, however, that traffic is invariably light on source route B during the rush hours we observe. For example, for observations collected during rush hour on Thursday, June 16, 2005, the relevant portion of source route B was entirely unoccupied 72% of the time. In contrast, source route A is never unoccupied.

6

Table 1: Summary Statistics of Traffic Behavior by Source Route

| | Source Route | | | |
| | A | | C | |
	n	%	n	%
Total Observations	2047	100.00	1065	100.00
Observations during rush hour	1487	72.64	584	54.84
Motorists Whose Destination Route is Observed	1493	72.94	1065	100.00
Motorists Observed to take Route A'	1370	91.76	589	55.31
Motorists Observed to take Route B'	123	8.24	476	44.69
Motorists Whose Destination Route is not Observed	554	27.06	0	0.00
Dates of Observation	5-5-05, 6-16-05 6-17-05, 10-26-05		6-10-05, 6-17-05, 10-21-05 10-26-05, 10-27-05	
Days of the Week	Weds, Thurs, Fri		Weds, Thurs, Fri	
Times of Observation	4:30 - 6:30 P.M.		4:30 - 6:30 P.M.	

relatively-fast moving. In lane M or R, a motorist can travel the distance between points X and Z in, on average, less than 60 seconds.
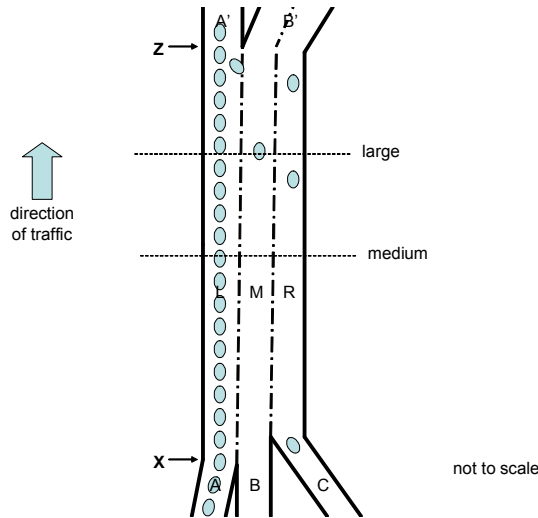

Figure 2: Typical Rush-hour Traffic Pattern

A third and central feature of our data is that, despite the considerable time savings, motorists from source A very rarely skip the line of traffic in lane L. Table 2 summarizes rush hour traffic behavior, by source route and vehicle type.[23] We classify the behavior of motorists who eventually chose to take route A' into three categories: those who did not skip lane L, those who skipped a medium-sized portion of lane L, and those who skipped a large portion of lane L. Specifically, motorists from source route A that never

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[23] The angle of the video camera and the large distance between points X and Z in Figure 2 precludes simultaneous observation of the behavior of drivers from source lanes A and C. Instead, we focus on one source route at a time and follow (by zooming the camera's lens) those drivers who may either be skipping the line and taking route A' or choosing the alternative route B'.

left lane L and motorists from source route C that entered lane L before the dashed band marked medium in Figure 2 were classified as having not skipped the line.[24] Those that cut into lane L at a point beyond the "medium" band but before the "large" band were classified as having skipped a medium-sized portion of the line. Those that cut into lane L at a point beyond the "large" band were classified as having skipped a large portion of the line.[25] The results in Table 2 indicate that among motorists who enter the confluence from source route A and eventually travel on route A', 93.8% never leave lane L. In other words, despite the substantial time savings available, just 6.2% of drivers from source route A skip any portion of the line.

This apparently other-regarding behavior of motorists from source route A contrasts with that of motorists from source route C. Unlike route A motorists, route C motorists quite often use lanes M and R to travel past the vehicles in lane L and then enter the line of traffic in lane L at a point very close to its terminus. More specifically, Table 2 shows that among those motorists from source route C who eventually choose route A', approximately 83.8% skip at least a medium-sized portion of the line in lane L; and 57.8% skip a large portion of the line.

Table 2: Summary Statistics of Rush Hour Traffic Behavior by Source Route

| | Source Route | | | |
| | A | | C | |
	n	%	n	%
Total Observations	943	100.00	584	100.00
Observations That Take Route A'				
Don't skip lane L	804	93.8	51	16.2
		(0.82)		(2.08)
Medium skip of lane L	6	0.7	82	26.0
		(0.28)		(2.47)
Large skip of lane L	47	5.5	182	57.8
		(0.78)		(2.78)
Total	857	100.00	315	100.00
Days of the Week	Weds. and Thurs.		Weds., Thurs., Fri.	
Times of Observation	4:55 -5:55 P.M.		5:00-5:55 P.M.	

Standard errors are in parentheses.

2.1.1 Stability

Despite the sometimes considerable distance in time between filming episodes, these qualitative features of the rush hour traffic pattern are remarkably stable across observation days. The variation in skipping

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[24] In practice, the "medium" band was marked by a road sign that hangs over the confluence approximately 0.2 miles from the point at which the three source routes are joined. We observed no vehicles from source route A that left lane L and re-entered at a point before the "medium" band.

[25] In practice, the "large" band was marked as 10 cars (or approximately 150 feet) beyond the "medium" band.

rates within source route, across filming days is modest. Recall that, on average, 6.2% of motorists from source route A skip any portion of the line. During the rush hour when the largest fraction of source route A motorists skipped, May 5, 2005, the corresponding figure was 8.6%. The pattern for source route C is similarly stable. On average 83.8% of source C motorists skip at least a medium portion of the line. During the rush hour of June 10th, 2005, when the rate of skipping among route C motorists was lowest, the corresponding figure was 76.5%. Thus, these data indicate that the differences in the patterns of rush hour skipping behavior between source routes are quite stable over time.

2.2   Heterogeneity and Non-random Selection

The data summarized above indicate profound differences in the behavior of motorists depending on their source route. The formal analysis of these behaviors that we present in Section 3 assumes selection into source routes A and C (what we will call "left-" and "right-laners") is random; that is, the choice between these routes is unrelated to underlying motivations regarding delay. It is possible, however, that left- and right-laners behave quite differently because they are inherently different; they work in different places and for that reason arrive from different source routes, and they also have different preferences. In short, simple heterogeneity may explain the differences in behavior between source route A and C motorists. To investigate this possibility, we examined both the vehicle mix in these two source routes and the motorists' behavior by vehicle type.

Table 3: Traffic Mix by Source Route

| | Source Route | | | |
| | A | | C | |
	n	%	n	%
All Motorists Observed Taking Route A'				
Commercial Vehicles	90	6.6**	106	18.0
		(0.67)		(1.58)
Minivans	73	5.3**	46	7.8
		(0.61)		(1.11)
Pickup Trucks	110	8.0	47	8.0
		(0.73)		(1.12)
Sports Cars	86	6.3	28	4.8
		(0.66)		(0.88)
Sport Utility Vehicles	352	25.7**	103	17.5
		(1.18)		(1.57)
Not Otherwise Classified	659	48.1*	259	44.0
		(1.35)		(2.05)
Total	1370	100.0	589	100.0

Table 3 summarizes the vehicle mix for all observations who took route A', regardless of whether they were obtained during thick, rush hour traffic. There are two both statistically and qualitatively significant differences between the vehicle mixes in each of the source routes. Commercial vehicles are substantially more common in source route C and sports utility vehicles (SUVs) are substantially more common in source route A. Thus, if commercial vehicle drivers were much more likely to skip the line and SUV drivers were

9

much less likely, these differences in vehicle mix could explain some of the difference in behavior between source route A and C drivers.

To evaluate whether these differences in vehicle mix may explain the differences in behavior between source routes, we investigated the frequency of line skipping by source route, conditional on vehicle type. Table 4 presents the results of ordinary least squares estimates of the relationship between vehicle type and the probability of skipping at least a medium-sized portion of the line, by source route. The first specification in column (1) pools observations from source lanes A and C, the subsequent specifications estimate the same relationship separately for observations from source lane A and C, respectively. The pooled regression, in column (1), indicates that source route C drivers are, conditional on vehicle type, nearly 78 percentage points more likely to cheat than those in source route A. Thus, we find no evidence that observable differences in the vehicle mix can explain the differences in behavior between source route A and C drivers. Indeed, when we perform a counterfactual experiment and calculate the average predicted value (propensity score) from this regression assuming all motorists were in source route C, the source route A vehicle mix is predicted to skip the line slightly more often (84.2% of the time) than is the actual source route C vehicle mix (83.8%).

Although we find no evidence that observable heterogeneity can explain the differences in behavior between source route A and C drivers, there is another form of non-random selection that could account these differences. This second form would arise if those who are less willing to wait choose source route C prior to being observed. There is, however, little reason to think that this second form of selection obtains. First, if a motorist who would otherwise arrive from source route A strongly prefers not to wait, he may simply skip the line in lane L. There is no material reason to take an alternate route. In addition, if there is a non-material motivation for seeking this alternative route, motorists need not take I-76 West all the way up to the next exit, pay the toll, and then re-enter from 76 East (source route C). Instead, such motorists could simply exit at King of Prussia Shopping Mall and take source route B.

While we find nothing to indicate that motorist heterogeneity between source routes A and C accounts for the differences in behavior between these two groups, there is evidence of systematic heterogeneity in preferences within source route. In particular, we find evidence that those driving minivans, sports cars and SUVs are more likely to skip some portion of the line, from both source routes. Specifically, in the pooled regression in column (1) of Table 4, the point estimates indicate that those driving sports cars skip at least a medium sized portion 15.6 percent more of the time than those driving cars in the omitted category, "not otherwise classified." Motorists in SUVs skip 5.6 percent more often and, minivan drivers skip 6.3 percent more. These estimates imply especially large differences in levels of skipping by vehicle type among source route A motorists. Sports car drivers from source A are, for example, more than six times more likely to skip than those not otherwise classified in the same lane. Minivan drivers in that lane are nearly three more likely to skip. When the relationship between vehicle type and skipping probability is allowed to vary by source route, in columns (2) and (3), these findings largely persist. The exception is that, among source route A

Table 4: OLS Estimates of the Relationship Between Vehicle Type and the Probability of Skipping the Line, by Source Route

	(1)	(2)	(3)
Covariates	a large skip of the line		
Source Route C Motorist	0.781**		
	(0.023)		
Commercial Vehicle	0.041	0.009	0.079
	(0.030)	(0.029)	(0.056)
Minivan	0.063*	0.071*	0.046
	(0.038)	(0.040)	(0.084)
Pickup Truck	0.048**	0.007	0.152**
	(0.023)	(0.023)	(0.055)
Sports Car	0.156**	0.154**	0.157**
	(0.039)	(0.045)	(0.065)
SUV	0.056*	0.053**	0.059
	(0.022)	(0.022)	(0.068)
Constant	0.024**	0.030**	0.787**
	(0.010)	(0.009)	(0.035)
Source Routes	A & C	A	C
Ave. of dependent variable	0.270	0.062	0.838
N	1172	857	315
R2	0.610	0.036	0.022
Propensity Score for Lane A Motorists	0.842 (0.002)		
Propensity Score for Lane C Motorists	0.838 (0.002)		

motorists, those driving pickup trucks are no more likely to skip the line, while pickup drivers from source route C are substantially more likely to skip. Taken together, these results suggest important heterogeneity in tastes resulting in substantial differences in behavior within source route.

2.3 Safety Concerns and the Risks of Skipping

Another potential explanation for the differences in behavior between source route A and source route C motorists is that those in source route A are more concerned that, by leaving their lane to skip ahead in line, they will subject themselves to the risk of a collision with a driver from source route B. Of course, source route C drivers who seek to change lanes are also subject to this risk but they are typically moving at a faster initial speed than route A drivers and thus, perhaps, less at risk of an accident. To evaluate the possibility that this safety concern is determining the differences in behavior, we examined both the level of traffic from source route B and the relationship between that level and the likelihood that a source route A

driver leaves his/her lane. Due to the inherent data collection limitations described above (see footnote 23), the choices examined here are binary; for this analysis we simply observe whether a route A driver exited lane L within 30 yards of the point of juncture (point X on Figure 2). Thus, in these data we cannot observe whether they actually skipped the line to take route A', or merely took the alternative route B'.

This part of the analysis is based on observations of 49 minutes of rush hour traffic on June 16, 2005, reflecting the activity of 540 motorists from source route A and 303 from source route B. The first important feature of the traffic pattern is that the relevant portion of source route B is entirely empty most of the time. Specifically, during this rush hour, the observable part of the lane (approximately 150 yards prior to the juncture point X) was free of motorists 72% of the time. A second important feature of these data is that the time intervals when the lane is unoccupied are substantial in size. The average length of the unoccupied time intervals is 19 seconds, and sometimes longer than a minute. In other words, there are many, substantial opportunities to enter the middle lane from the left lane without concern for traffic from source B. The third relevant feature of the data is that the likelihood that a route A driver leaves his lane is not much related to the level of source B traffic. We divided the rush hour into 23, approximately 2 minute, intervals and calculated both the fraction of that interval that the relevant portion source route B was occupied by at least one motorist and the probability that a source route A driver left his lane. Over the entire rush hour, 16.8 percent of route A motorists leave their lane.[26] The correlation between the fraction of the interval in which source route B is occupied and the likelihood of a source route A driver leaving his lane is quite low (0.046) and indeed positive, though not statistically significant. Viewed more completely, Figure 3 depicts the relationship between the traffic level in source route B and the likelihood a source route A driver leaves his lane, by two-minute time interval. The fitted values from a univariate regression are also displayed in the figure. Here again we see no evidence that source route A drivers are more likely to leave their lane when the middle lane is clear. These findings suggest that it is unlikely that a fear of being rear-ended is what motivates most source route A drivers to remain in line.

It is also possible that a fear of being rear-ended motivates route C drivers to keep moving up the line, rather than taking the first opportunity to merge in. If merging places the motorist at risk because he must slow down in lane M, then he may continue to move slowly ahead waiting for an easy opportunity to enter the line. We investigate this possibility by examining evidence on the behavior of source C drivers just before and just after rush hour when the line is short, but still fairly slow, and therefore delays are non-trivial. In these cases, there is no risk of getting hit from behind if one takes the earliest opportunity to enter the left-lane, but the delay costs remain substantial, though on average less than the typical rush hour delay. We can compare behavior in these circumstances to that when the line is moving similarly fast, but is sufficiently

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[26] Given that approximately 17% of observations leave lane L within 30 yards of the juncture point, and (on a different day) we observed approximately 8% of source route A drivers skipping the line, we may infer that approximately a half of those we observe leaving lane L eventually skip the line.
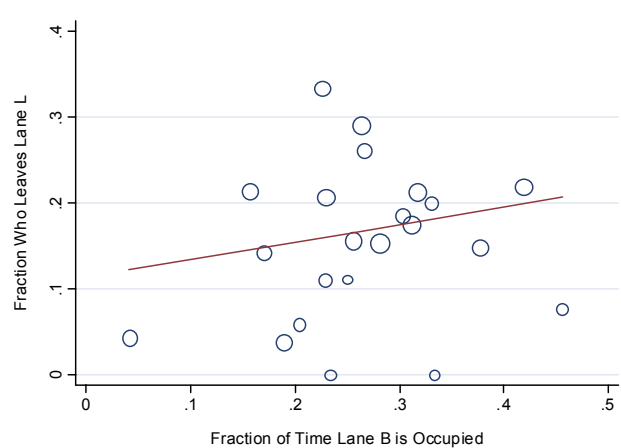
Figure 3: Fraction of Source A Motorists Who Leave Their Lane, By Level of Traffic in Source Lane B, June 16, 2005. Unit of Observation is a Two-Minute Time Interval, Weighted by the Number of Source Route A Motorists in the Interval.

long as to leave no open space at its end. We find no evidence that conditional on delay, source route C motorists behavior is different when they have easy access into the left-lane. More specifically, when we regress the decision to skip a large portion of the line[27] on a third-order polynomial in expected delay from waiting the left-hand lane from its beginning to its end, and an indicator for whether the line is sufficiently short to leave an open space for entry at its end, the coefficient on this short line indicator is 0.005, with a standard error of 0.028. Thus we find no evidence that a concern for safe entry into the left-hand lane is dictating the decisions of source route C motorists.

Finally, it is possible that there are important physical risks of entering the line upon skipping, especially a large portion of the line. Motorists waiting near the beginning of line may attempt to refuse a driver entry, and thus force him either to wait or take the alternate route B'. Alternatively, motorists in line may punish the would-be skipper by damaging his car in an act of "road rage." These potential risks of skipping may make waiting optimal for left-laners but not for right-laners, who must enter the line somewhere if they are to take route A'. In fact, we see no evidence that entering the line is physically risky. The typical wait for a motorist trying to enter very close to the line's terminus is just one or two cars. Moreover, members of the PennDOT team that monitors this location by video and alerts State and local police in the event of an accident, reported to us that there have been no accidents warranting a call to police in their memory; this despite approximately 350,000 motorists passing through this location just during rush hour each year. We therefore find no evidence that the physical risks of skipping can explain the difference in behavior between source routes.

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[27] When the line is short it is sometimes impossible to skip merely a medium portion of the line.

2.4 Serial Correlation in Decisions

Another notable feature of the data is the positive correlation between the choices of motorists in immediately adjacent positions on the source route line. More precisely, our observations of source route A indicate an important positive serial correlation in driver choices, largely truncated after one lag and entirely truncated after three lags. Table 5 displays the correlations between the choices of motorists in position π on source route A, and the choices of those preceding them on the route by x positions. Again, due to data collection limitations, the choices examined here are binary. Here we observe only whether the driver left lane L within 30 yards of the point of juncture, and not whether he or she actually skipped the line to take route A', or merely took the alternative route B'. Among the 540 motorists for whom we have sufficient information, the decision of a driver in position π and that of the driver just preceding him in position $\pi - 1$ has a statistically significant, positive correlation ($\rho = 0.129$). The correlation between the decisions of motorists separated by one vehicle is considerably smaller and not statistically significant ($\rho = 0.053$), while the correlation between the decisions of motorists separated by two vehicles is still positive and borderline significant ($\rho = 0.080$). We find, however, no significant positive correlation in the decisions of motorists separated by more than three vehicles. Indeed, the decisions of motorists separated by more than five vehicles are negatively correlated (though these correlations are not statistically distinguishable from zero at the 5% level).

Table 5: Correlation of the Decision to Leave Lane L with that of Drivers x Positions Ahead.

	п	п-1	п-2	п-3	п-4	п-5	п-6	п-7	п-8	п-9	п-10
п	1.000	0.129**	0.053	0.080*	0.036	-0.018	-0.072	-0.005	-0.084*	-0.030	-0.024

* Significant at the 10% level. ** Significant at the 5% level.

Figure 4 presents an alternative view of the relationship between the decisions of motorists separated by relatively few cars. This figure displays the probability that a motorist leaves lane L, conditional on the motorist x positions ahead leaving lane L. The probabilities have been rescaled so that the unconditional probability of leaving lane L (0.168) equals zero. Here again we see that probability of a motorist leaving lane L is considerably higher if the motorist just preceding him left the lane. This differential probability of leaving the lane drops to essentially zero when three cars separate the two drivers, and becomes negative when the drivers are separated by more than four cars. Thus, we see still more evidence that decisions of near neighbors on the line are correlated.

As before, when we considered simply the decision to leave lane L, it is possible that this serial correlation in decisions is driven by concerns for safety rather than by any concerns for the outcomes or opinions of others. In particular, it is possible that if a motorist decides to leave lane L, the subsequent motorist is more likely to observe the same window of opportunity to safely leave the lane, a window which closes before
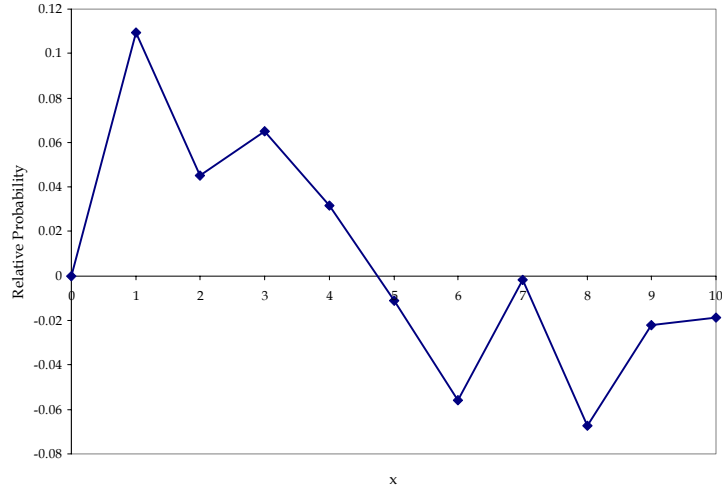
The vertical axis measures the normalized probability a driver leaves lane L, conditional on a driver x positions ahead leaving land L. The vertical axis is rescaled so the unconditional probability of leaving lane L equals zero.

Figure 4: Relative Probability of Leaving Lane L, Conditional on Driver x Positions Ahead Leaving, 6-15-05, N=540

the next driver or two can also leave. However, recall from subsection 3.5 that the intervals of time when lane B is unoccupied are both many and quite long. There are thus many opportunities for more than two drivers to leave the lane at the same time. Moreover, if a motorist finds a safe opportunity to leave lane L which then quickly closes, on average his immediate followers need only wait a few seconds for another large window of opportunity to open. These patterns of the data thus indicate that it is unlikely that concerns for safety can account for the serial correlation in the decisions of route A motorists to leave their lane.

2.5   The Response to Changes in Material Payoffs

Much of the preceding analysis suggests that the behavior of, especially source route A, motorists in this setting is not dictated by concerns for material payoffs alone. Almost all source route A drivers, and even some source route C drivers, forgo substantial time savings by waiting in the line to exit. Nevertheless, these data also indicate that the rate at which motorists choose to skip the line depends on the material payoffs (the delay avoided) from doing so.

Figure 5 presents the relationship between the expected delay from continuously waiting in the left-hand lane during rush hour, and the likelihood of skipping a large portion of the line in that lane. More precisely, 5 shows, in blue and scaled on the right, the fraction of source route C drivers who choose to skip a large portion of the line as a function of the average expected delay from waiting in lane L from the point of juncture to the terminus, for 55 rush hour time intervals, each of 2 minutes in length.[28]   In

[28]Here, the expected delay (ED) within an interval is calculated by meauring the average time required for a motorist to travel

15

red and scaled on the left, we present the average expected delay from waiting in lane L and the fraction of source A motorists who leave lane L, for 45 rush hour time intervals, each of approximately 2 minutes in length.[29] The figure also presents, for both sets of observations, the predicted values from a univariate linear probability regression with expected delay as the independent variable and fraction skipping a large portion of line as the dependent. In each case both the coefficient on expected delay in these regressions is statistically distinguishable from zero at the 10% confidence level, and in the case of lane A, the coefficient has a p-value of 0.002. These data suggest that the fraction skipping the line is increasing with delay. As
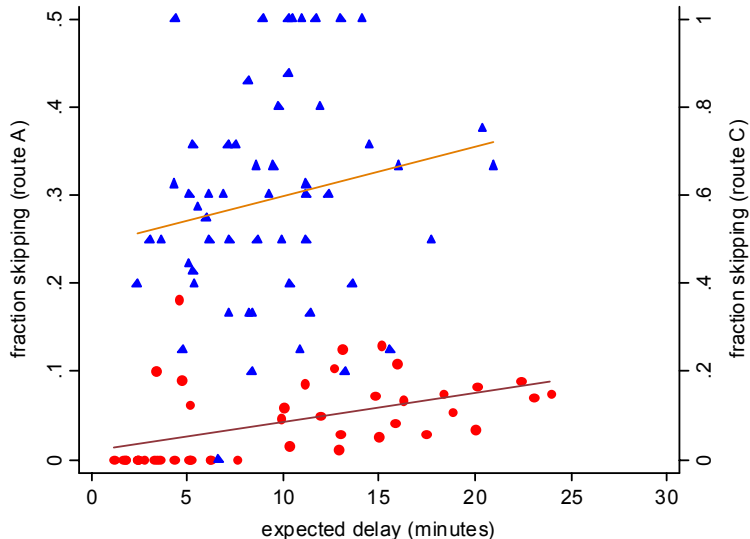

Figure 5: Expected Delay and the Fraction Skipping a Large Portion of the Line

expected, the average levels of skipping are considerably higher for source route C motorists at every level of

from the point of juncture to the green signs overhanging the highway, and multiplying that number by 3.75. To reduce noise, we then smooth this figure across adjoining intervals so that the delay assigned to interval t equals $0.2ED_{t-1}+0.6ED_t+0.2ED_{t+1}$. Again, to reduce noise, nine intervals with fewer than five observations are excluded from the analysis. Neither adjustment affects the qualitative relationship between lane speed and the proability of lane skipping, but these adjustments permit more precise estimates of that relationship.

[29]Here the expected delay is calculated in one of two ways, depending on the camera angle. The first method is exactly the same as that just described. The second method, which is used for approximately half of the intervals, calculates lane speed from the number of motorists traveling past a single point on the road during a two minute interval. This figure is multiplied by 15 to obtain an estimate of feet per minute. The inverse of that number is multiplied by 0.6*5280 to estimate the time from juncture to terminus. When motorists leave the lane the measured speed of the lane increases mechanically. This has a relatively large effect on measured speed when traffic is otherwise moving slowly. The cars per minute measure is therefore adjusted so that the numerator includes only cars that didn't leave the lane. In addition, two intervals with seemingly implausible estimated expected delays exceeding 45 minutes are excluded. Neither adjustment affects the qualitative relationship between lane speed and the probability of leaving the lane.

16

delay, but each set of motorists tends to skip more as the material incentives for skipping the line increase.

Further evidence consistent with motorists responding to material incentives comes from an investigation of behavior just before and just after rush hour. During these times, the line of traffic in lane L is just forming or dissipating and moves much faster than during rush hour. During these times, when the average expected delay is 90 seconds, and always less than 6 minutes, we find that the rate of line skipping is substantially lower among both source route A and source route C drives. Among the nearly 513 motorists from source route A whom we observe taking route A' outside of rush hour, just 9 (1.75%) skip some portion of the line. Of 274 source route C motorists we observe taking route A' outside of rush hour,157 (57.3%) skip some portion of the line. Thus we see that skipping behavior is significantly lower when the material incentives for doing so are unusually low.

3   The Performance of Existing Models

To evaluate existing theories of other-regarding behavior we want to develop a formal framework with the following three properties: First, the framework should capture the essential elements of the traffic choices described in section 2. Second, the framework should be sufficiently flexible so as to nest each of the existing formal models of other-regarding behavior. Finally, the framework should be sufficiently general so as it may be translated with relative ease to other settings and other behaviors. The following develops one such framework and describes possible extensions.

This is a simultaneous-moves, large game. There are two populations, left-laners and right-laners, of mass L and R, respectively. In our data, left- and right-laners map into drivers from source routes A and C, respectively. The initial endowment of a driver is given by $w \geq 0$, denoting the amount of time he has already waited in line before the moment we observe the game being played.[30] The endowments of left-laners are distributed according to $F_L(w)$. The right-laners' distribution of endowments is denoted by $F_R(w)$. We assume that $F_L(w)$ stochastically dominates $F_R(w)$, which means that on average right-laners have shorter initial waits. A special case of interest is that in which the right-laners have no initial waiting time; in that case, each right-laner has the same endowment, $w \equiv 0$.

Further, motorists are characterized by unobservable heterogeneity, denoted by the real number a. The parameter a, which we will refer to as altruism, is meant to capture the degree to which each motorist trades off material benefits with non-material considerations. This parameter will reflect heterogeneity in cost of time, in willingness to follow a norm, etc. We assume that the parameter a is distributed across motorists independently of whether they are left or right laners, which implies that there is no selection of motorists according to this unobservable characteristic. It also implies that a and w are distributed independently.

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[30] In practice, w will be identified with the amount of time spent waiting before the first opportunity to skip the line presents itself.

Left-laners are initially distributed among places in line, represented by the integers $\pi \in \{1, ..., n\}$, where position 1 is beginning of the line (closest to the desired exit) and position n is its end. For now, we need not specify the density of that distribution. Right-laners have $\pi = n$. All players simultaneously choose a position $p \in \{1, ..., n\}$. Players may choose any position, including their initial position ($p = \pi$), or a position further back in line ($p \geq \pi$).

Let $\lambda(p, w)$ be the fraction of left-laners with endowment w choosing p, and $\rho(p)$ be the fraction of right-laners choosing p. Denote with

$$\mu(p) = L \cdot \int \lambda(p, w) \ dF(w) + R \cdot \rho(p) \tag{1}$$

the total mass of motorists choosing p. The total delay for a motorist with an endowment w who chooses p is

$$D(w, p, \mu) = w + \frac{\mu(p)}{2} + \sum_{i < p} \mu(i). \tag{2}$$

Clearly, the function $D(w, p, \mu)$ is increasing in p. The delay of the motorist who is last in line is simply $L + R$. The average delay is $(L + R)/2$.

For future reference, note that the model makes no mention of the speed at which the line moves, i.e., of the rate at which cars pass through A'. In practice, depending on the exit rate a given choice of place in line can result in very different delays. The effect of a slower exit rate can be captured formally in our model by scaling up the parameters L and R. By increasing these parameters, a given choice of p will result in a greater delay D (see equations 1 and 2).

Nash equilibrium quantities are henceforth denoted with a * superscript.

3.1 Own Payoffs Only

As a benchmark, we first consider the canonical case where motorists are concerned only with own payoffs—the standard assumption in most economic models. The motorist's material payoff is

$$u(w, p, \mu, a) = g(D(w, p, \mu), a).$$

We will henceforth maintain the following assumption.

Assumption 1 *g is decreasing in its first variable for all a.*

This assumption means simply that lower delay provides greater material payoff. This formulation allows that g is concave in D and so the utility cost of delay increases with the delay.[31]

Because g is decreasing, any motorist's optimal action is to choose $D = 1$, i.e., jump to the head of the line.

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[31] In an extended model, we could also allow an extra, social, cost of delay if some motorists who were not initially located there, chose to occupy the head of the line ($\pi > 1$ and $p = 1$).

Proposition 1 *If own payoffs are the motorists' only concern, then every motorist's best response is to skip the entire line.*

Because, as documented in Table 2, a large fraction of (especially source A) motorists do not skip the line, this proposition indicates that the model with purely material payoffs does not accurately fit our data.

3.2   Efficiency Concerns

We should consider the possibility that, in addition to the factors introduced above, motorists are also public spirited in the sense that they care about the effect of their actions on efficiency, over and above distributional considerations.[32] If, for example, congestion effects cause the act of skipping the line to add materially to the aggregate exit time, a motorist who cares about efficiency might refrain from skipping the line. While in general this may be a relevant concern, in our case this consideration does not help to rationalize the motorists' behavior as best responses. Let us see why not.

First, efficiency concerns cannot plausibly account for the large fraction of left-laners who do not skip the line. During rush hour, traffic moves so slowly that if one more individual skipped the line the rate at which the line moves would be essentially unchanged. The possible exception would be the case in which motorist were to go to the very head of the line, and possibly hamper the prompt egress from exit A'. But then an efficiency-concerned motorist would simply choose to deviate by skipping slightly less than the full line. Second, even if skipping the line decreased the speed of exit, concerns for efficiency do not explain the difference in behavior between left- and right-laners (unless, of course, that concern were more frequent among left-laners).[33] These observations indicate that postulating some concern for efficiency does not help explain our data.

3.3   Concerns for Relative Position

We now begin to consider, more formally, the ability of "social preferences" to explain the data by augmenting the canonical preferences of subsection 3.1 with a direct concern for relative position. Given the equilibrium strategies $\lambda(p, w), \rho(p)$, we can compute the distribution of delays in the population. Let $H_{\lambda,\rho}(d)$ denote the fraction of the population with a delay smaller than d. A motorist who has delay d and cares about his relative position will care about $H_{\lambda,\rho}(d)$. We therefore write the augmented utility function

$$\tilde{u}(w, p, \lambda, \rho, a) = \tilde{g}(D(w, p, \mu), H_{\lambda,\rho}(D(w, p, \mu)), a).$$

A concern for equity can be captured by having $\tilde{u}(w, p, \lambda^*, \rho^*, a)$ be concave in p, which means that the marginal utility from delay is decreasing in the level of delay already obtained. Thus, relative to an individual

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[32]Charness and Rabin (2002) emphasize this motivation as an important factor in explaining laboratory behavior.

[33]Indeed, to the extent that a concern for efficiency were relevant, it could be captured by an appropriate modification of the function sentiment function introduced below in Section 3.5, and the analysis there would apply.

with a large delay, an individual with little delay will suffer less (and possibly even enjoy) increasing his delay by a given amount. This formulation nests, among other things, the inequality aversion formulated in Fehr and Schmidt (1999) and Bolton and Ockenfels (2000). It may be assumed that $\tilde{g}$ is decreasing in H when H is large, because concerns for relative position most likely lead those who are quite unfavorably situated to have a greater preference for reducing their delay.

This model is unable to account for the large difference in other-regarding behavior between left and right laners, which is highlighted in Table 2. To see this, observe that $\tilde{u}(w, p, \lambda, \rho, a)$ only depends on the motorist's identity through w and a, and not directly on whether the motorist is a left- or a right-laner. By assumption, a is distributed identically between left and right laners (and the findings in Section 2.2 above bear this out empirically). The left-laners' "excess" of other-regarding behavior must, therefore, be ascribed to their greater w. According to this model, then, if left-laners skip less often than right-laners it is because they have waited longer before coming to the merging point. This seems counterintuitive, for we would expect that if two motorists choose p to maximize the same function $\tilde{u}(w, p, \lambda^*, \rho^*, a)$, and the left-laner starts out with a longer wait $w_L > w_R$, then he will choose a correspondingly lower $p_L < p_R$ so that both players end up with the exact same delay. In fact, it can be proved formally that, if $\tilde{u}(w, p, \lambda^*, \rho^*, a)$ is single-peaked in p, then motorists with a bigger w will choose a lower p. However, if the function $\tilde{u}(w, p, \lambda^*, \rho^*, a)$ is not single-peaked, then motorists with a bigger w might choose a bigger p.

To investigate the possibility that non-single peaked preferences are responsible for the greater patience of left laners, we investigate empirically the effect of w on cheating behavior. Ideally, we would like to fix λ^*, ρ^*, and a, and then observe how the optimal p varies with w. In practice, our strategy will be to take advantage of the variation that exists in the length of the left-lane line prior to crossing point X. This line is sometimes very short, particularly at the early and late stages of rush hour, and is very long at other times, typically in the midst of the rush hour. We therefore regress the fraction of motorists cheating on an indicator ("short line") for whether a left-laner experienced an initial wait of approximately zero. In those cases, left and right laners are indistinguishable according to the model, and should behave identically. Empirically, the social preferences model presented here indicates that the variation in cheating should be fully accounted for by the indicator variable. Table 6 presents the results of the regression. Note that we control for the speed of the line, because theoretically λ^* and ρ^* depend on the speed of the line, and also because in practice the relation between p (the place chosen in the line, which our data record) and D (the delay incurred by the motorist, which is the choice variable in the model) is affected by the speed at which the line moves.

Table 6 reveals that the coefficient for the indicator variable "short line" is small in magnitude, is never significant, and moreover its introduction does not materially change the effect of the dummy that records whether a motorist came from lane C. Empirically, then, we conclude that models of relative position cannot account for the observed difference in behavior between left and right laners.

Table 6: OLS Estimates of the Relationship Between the Probability of Skipping, Source Route, Expected Delay and Initial Waiting Time

	(1)	(2)	(3)	(4)
Covariates	a large skip of the line			
Source Route C Motorist	0.481**	0.487**		
	(0.028)	(0.028)		
Short line		-0.043	-0.005	0.017
		(0.057)	(0.007)	(0.126)
Expected Delay	0.074**	0.060**	0.010	0.092*
	(0.021)	(0.026)	(0.007)	(0.056)
$(\text{Expected Delay})^2$	-0.005**	-0.004*	-0.0004	-0.007
	(0.002)	(0.0026)	(0.0008)	(0.006)
$(\text{Expected Delay})^3$	0.0001**	0.0001	0.000006	0.00017
	(0.000)	(0.000)	(0.00002)	(0.00018)
Constant	-0.191**	-0.148**	-0.011	0.225
	(0.049)	(0.063)	(0.013)	(0.158)
Source Routes	A & C	A & C	A	C
Ave. of dependent variable	0.336	0.336	0.036	0.507
N	146	146	53	93
R2	0.599	0.600	0.343	0.212

3.4 Reciprocity

Existing models of other-regarding behavior allow not only a direct concern for relative position, but also a psychological concern for how others will perceive the intentions behind one's actions. Charness and Rabin's (2002) "reciprocal fairness equilibrium" postulates that every player maximizes a weighted function of her own and of the opponents' material payoffs. The weights assigned to the opponents' payoff are endogenously determined, and they depend on their equilibrium behavior. In our setting, players would assign a larger weight to the payoffs of those opponents who behave in a public-spirited way, i.e., whose behavior suggests that they themselves place a large weight on the opponent's payoffs. Opponent who appear to behave selfishly will receive a low weight in our player's objective function, or even worse, may receive a negative weight, meaning that our agent will wish to spite them.

Charness and Rabin's (2002) model is not directly applicable to our setting because it does not allow for heterogeneity across players. Nevertheless, we can ask if an explanation in the spirit of that model fits the data. According to the reciprocity hypothesis, motorist who refrain from skipping the line are reciprocating the good behavior of the motorists who wait patiently in line. Conversely, upon seeing many motorists deviate, a motorist would be more inclined to cheat herself. Our data show some support for the latter implication, in the form of a mild positive correlation between deviants (see Section 2.4). The reciprocity

hypothesis does not account for the negative portion of the correlation structure, however. Moreover, the main feature of our data, the difference in behavior between left and right laners, cannot be explained by the reciprocity hypothesis. In order to explain the difference in behavior between left and right laners, we must posit that a motorist in the left lane has a more favorable view of the sacrifice made by those who stay in line, and is therefore more inclined to return the favor. Since the only payoff-relevant characteristic that distinguishes left and right laners are the waiting times w, it must be that the longer a motorist has waited, the more likely he is of viewing those who are in line as being selfless and deserving. While this hypothesis is intriguing, it is contradicted by Table 6, which shows that, conditional on source route and total delay, time waited in line does not materially affect the probability of cheating. We conclude that, while the data can be interpreted as showing some support for a reciprocity hypothesis, reciprocity cannot account for the bulk of the variation we observe in our data.

3.5 Cold Prickle and Other Psychic Consequences of Overtaking

We may also consider the possibility that, in addition to the factors introduced above, motorists derive a "warm glow" from charitable acts or, alternatively, a "cold prickle" from uncharitable ones. This means that motorists may derive psychic value simply from the act of not skipping the line. To incorporate such an effect, observe that the act of overtaking the motorists between points π and p in the line results in $D(0, \pi, \mu) - D(0, p, \mu)$ motorists being overtaken. Let us define the function

$$S(w, D(0, \pi, \mu) - D(0, p, \mu), a) \geq 0,$$

which depends on w and on the mass of motorists that are being overtaken.[34] The function S, which we will take to be decreasing in its second argument, represents the motorist's sentiments from skipping the line between his initial position π, and p. The augmented utility function is now

$$\widetilde{\widetilde{u}}(w, p, \lambda, \rho, \pi) = \widetilde{\widetilde{g}}(w + D(0, p, \mu), H_{\lambda, \rho}(w + D(0, p, \mu)), S(w, D(0, \pi, \mu) - D(0, p, \mu), a)),$$

Again, note that under this model the only source of difference between right and left laners is the distribution of their w. Can this model rationalize the observed difference in behavior between left and right laners? Not unless we assumed that the sentiment is positively associated with time waited in line, i.e., that those who have waited the longest endure the coldest prickle from skipping the line behavior. While

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[34]The function S could also capture the negative sentiment of the motorists between π and p. (More generally, S could depend on the initial waiting times of the individuals between π and p.) Note that we are using μ, the ex-post distribution of individuals. Some of the overtaken motorists might themselves have overtaken others and are, therefore, not made worse off relative to their initial position. Nevertheless, these people will still harbor ill will toward the overtaker. An alternative formulation would have S reflect the ill will borne by motorists towards those who are in front of them in line, regardless of whether they skipped the line to obtain that position. Formally, this model would replace π with n in the S function.

it seems implausible that such an effect might be so powerful as to dictate left laners' behavior, it is not logically impossible. Table 6, however, shows that, conditional on source route, the time waited in line does not materially affect the probability of cheating. We conclude that these models of a psychological sentiment from skipping cannot account for the bulk of the variation we observe in our data.

3.6 Repeated Games Considerations

3.7 A Model of Ethical Agents

Each of the above models of other-regarding behavior is based on the premise of methodological individualism. Thus, these models have trouble explaining the profound difference in behavior between left- and right-laners. In this section we investigate a different type of model; a model that considers an agent's group identity as an important element of his circumstance, and allows for agents to prefer behaviors that benefit their group instead of only themselves. Here we build on ideas put forward in Feddersen and Sandroni (2002), who themselves build on Harsanyi (1977, 1980, 1992).

In a stylized version of our theory, following Feddersen and Sandroni, we imagine that each motorist feels a sense of belonging to a particular group. We assume that motorists who belong to a group choose a certain ethical rule that, they imagine, will be followed by all members in their group. Once an ethical rule for each group has been established, each agent chooses whether to follow his group's rule. This decision is determined by the agent's personal inclination to follow ethical rules, and by his material benefits from deviating from the rule. A group is assumed to choose the ethical rule that maximizes the aggregate welfare of its members, given the behavior of all other agents.[35]

With this in mind, we now turn to our specific application. We shall assume that all left-laners think of themselves as belonging to the same group. In contrast, we assume that each right-laner belongs to his own separate group, or—said differently—there are many groups of right-laners, each containing exactly 1 motorist. We shall also assume that, if a mass of motorists decides to take advantage and skip the line, then all motorists incur a loss in social utility which is an increasing function of the mass of motorists skipping. More precisely, we assume that there is no deviation that, when undertaken by the whole group, preserves efficiency.[36]

This stylized model can rationalize the profound difference in behavior between left- and right-laners. When evaluating deviations from an ethical rule, left-laners will consider the outcome that arises when all

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[35] This type of theory starts out from quantities that are largely observable, and yields a set of group-specific ethical norms, as well as observed behavior. What is left unspecified is the mechanism of group formation. The composition of groups is crucial. If, for example, all groups were singletons, then the predictions from this model would simply reduce to Nash equilibrium. On the other hand, if all agents belonged to the same group, then ethical rules might play a large role and observed behavior might be very different from Nash behavior.

[36] Note that this assumption is logically consistent with the notion that an individual deviation may always be chosen so as not to decrease efficiency, as the mass of one person's deviation is zero.

members of their group deviate in unison. Because of their large mass, left-laners anticipate that their choice of a more selfish ethical rule will cause members of their group to skip more often and will therefore generate a social loss (slower exit rate). This consideration provides a counterbalance to the material advantages that the group of left-laners, as a whole receives, from deviating. The ethical rule at which the two effects exactly counterbalance each other is the one that left-laners adopt. Right-laners, in contrast, have nothing to keep them in check, since there is no social loss attached to a single person deviation, and so ethical considerations do not apply. More precisely, the ethical rule for a right-laner prescribes that he should behave as is privately beneficial. Hence, in our simple model, right-laners will deviate more often than left-laners. These considerations are collected in the following conjecture.

Conjecture 1 *Suppose all left-laners identify with a single group, whereas right-laners do not feel part of any group. Then, the ethical rule a la Feddersen and Sandroni (2002) prescribes that all right-laners should deviate, and that left- laners should deviate less than right-laners.*

According to this conjecture, a model of ethical agents could (along with some distribution of altruism to accommodate the right-laners who do not skip) rationalize the difference in the skipping propensity of left- and right-laners. However, that simple model has difficulties explaining another feature of the data, namely, the correlation in the frequency of skipping behavior on the part of left-laners. To understand this statement, one must understand how the left-laners' skipping behavior is interpreted under the Ethical Model. In the Ethical Model, some skipping is expected in equilibrium; under the model, left-laners who skip the line are those who have a higher benefit from skipping (e.g., a high opportunity cost of time), or those who are less touched by ethical considerations. Note that, in our application, it is implausible to believe that there should be spatial correlation in the distribution of these traits (high cost of time, low ethics). That is, we should expect these traits to be randomly distributed along the line. Moreover, according to the ethical model, nothing of relevance should be inferred by agents from the fact that the motorist in front of me skipped the line. So, to the extent that we see a correlation in skipping behavior between first skipper and his successor in line, we cannot attribute this correlation to the ethical model. Of course, a positive correlation in skipping between first skipper and his successor in line is not difficult to rationalize; one can appeal to cascade effects due to any number of reasons. What is much more difficult to explain is why the correlation between second and third skipper should be lower than between first and second skipper. The difficulty is that, once his two predecessors have skipped, the potential third skipper is in exactly the same position as the second skipper was when the latter decided to skip, except that he has seen ever more people skipping, so that if anything he should be more inclined to skip than the second skipper, not less. This discussion is summarized in the following conjecture.

Conjecture 2 *A model of ethical agents a' la Feddersen and Sandroni (2002) has difficulty rationalizing the correlation in the left laners' skipping behavior.*

Despite this difficulty, we view the ethical agents model as the most promising, among those that are capable of rationalizing the other-regarding behavior, for explaining the behavior observed in our data. Drawing on evidence from the norm-adherence literature in social psychology, we propose to refine the simple model of ethical agents outlined above in order to accommodate better the correlation in skipping behavior. Moving forward, we could then test that model's ability to explain seemingly other-regarding behavior in other contexts.

4   Conclusion

To be added.

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